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Abstract

In our thesis, we analyze the transmission of monetary policy in the four largest Euro area economies, namely Germany, Italy, France and Spain. The focus of the analysis is to examine the heterogeneity and time variation in response to common monetary policy shocks for the period spanning from 2004:09-2016:12. For that purpose, we employ a data-rich environment along with a two-step factor-augmented vector autoregressive model (FAVAR), introduced by Bernanke, Boivin, and Eliasz in 2005. Moreover, in order to investigate the time-varying impacts of the policy effects and the impact of the financial and sovereign debt crisis on the transmission mechanism, we also use a rolling window technique. According to our empirical investigation using these methods, the thesis obtains the following main conclusions:

Firstly, the contractionary impact of the monetary tightening is heterogeneous for a majority of our measures, i.e. money supply, deposit liabilities and loans, while for most, the responses appear to be negative. Moreover, the impulse responses of monetary aggregate M1, deposit liabilities for households and lending for house purchase to monetary policy shocks are more heterogeneous than that of other key indicators. Throughout our analysis, we also observe a persistent difference in terms of heterogeneity between the core and the periphery of the EA. Among the financial indices, Spanish and Italian are surprisingly the least affected by the monetary tightening, while overall for our observed measures the responses appear to be the most homogeneous. Secondly, although the effects of the policy shocks on our whole sample approach mostly appear to be heterogeneous, we note that over time the transmission mechanism displays important differences. Namely, our rolling window estimations imply that the influence of the policy shock on our variables is rather homogeneous across countries for the period spanning from 2004:09-2014:07. At the same time, the last two rolling windows, or when moving into the crisis period, i.e. 2007:09–2015:07 and 2008:09–2016:07, evidently imply more heterogeneous impact of the shock. We believe that these findings are crucial in order to further investigate whether or not the Euro area monetary transmission process is uneven to such extent, that it could complicate the conduct of the single monetary policy.

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List of Abbreviations

AIC	Akaike information criterion
CPI	Consumer price index
DE	Germany
DFM	Dynamic factor models
DSGE	Dynamic stochastic general equilibrium
EA	Euro area
ECB	European Central Bank
ES	Spain
EU	European Union
FAVAR	Factor-augmented vector autoregression
Fed	Federal Reserve
FR	France
GDP	Gross domestic product
HICP	Harmonized index of consumer prices
HQ	Hannan-Quinn
IP	Industrial production
IT	Italy
MA	Moving average
MFI	Monetary financial institution
Non-MFI	Non-monetary financial institution
NFC	Non-financial corporations
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary least squares
PC	Principal components
PPI	Producer price index
REFI	ECB official refinancing operation rate
SIC	Schwarz information criterion
UK	United Kingdom
US	United States
VAR	Vector autoregression

1   Introduction

This thesis investigates the monetary transmission mechanism in the largest economies in the Euro area (EA), namely Germany, Italy, France, and Spain. In particular, our attention is focused on the impacts of monetary policy shocks across countries and over time. In the first part of our research, we investigate the question of heterogeneity in the effects of common monetary policy shocks for credit institutions on aggregate, long-term government bond yields, monetary aggregates and financial sector equity prices.[1] For the latter, we use a data-rich environment along with a two-step factor-augmented vector autoregressive (henceforth FAVAR) technique, proposed by B. S. Bernanke et al. (2005). In the second part, we enhance our finding, by adopting a rolling windows approach, which captures time-varying impacts of the policy shocks and the effects of the global financial and sovereign debt crisis on the transmission mechanism in the EA. To investigate both heterogeneity and the time variation effect, a novel data set spanning the period from 2004:9-2016:12 is used.

Our essay contributes to the limited number of studies in regard to heterogeneity in the EA. To the best of our knowledge, we are the first to study if there is heterogeneity in the effects of monetary policy shocks on balance sheet items of credit institutions while adopting a FAVAR approach. Also, we are among the few to adopt monetary financial institutions (MFIs) data. In our research, we will not go as far, as to see how monetary policy affects the macroeconomy via the bank lending channel,[2] but we will focus on the following questions: is there any asymmetry in how single EA financial sectors respond to the common monetary policy decided by the ECB? How are monetary policy shocks transmitted to the financial sector equity prices? Is there heterogeneity in how EA credit institutions

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[1] The choice of the countries was partly dictated by the issues of their systemic importance to the EA, in addition to the respective financial systems being still largely bank based rather than market based.

[2] For a detailed overview of the bank lending channel literature see Gambacorta and Marques-Ibanez (2011).

balance sheet items respond to the common monetary policy? What explains differences in individual responses to monetary policy shock? Does the transmission change over time?

There is no doubt that one of the major focuses of monetary economics has always been to quantify and analyze monetary disturbances in terms of their effects on various sectors of the economy. Similarly, the understanding of the transmission mechanism has always been important for the monetary policy of financial regulators around the world, even more so after the financial crisis. The necessity of understanding was made even more evident through the economic turmoil that highlighted both "the importance for banks to have sound financial conditions and for monetary policy rate cuts to effectively curb the contraction in the credit supply to the economy."[3] Not surprisingly then, the role of banks and the transmission mechanism has been studied extensively both on an empirical and theoretical level, with the EA being the prime source of interest.

Before the single currency was introduced, all member states' central banks had different agendas in regard to the objectives for containing inflation and boosting economic growth (Mihov, 2001). However, everything changed after 1999 since the ECB took over the direction from the national central banks and imposed a common monetary policy. Nowadays, despite significant differences in economic structures, legislation, fiscal policies, and debt levels between sovereign states, all are subject to a single monetary policy. Such circumstances make it particularly difficult for the ECB to conduct its monetary policy as the reactions may differ from country to country. It is then natural to ask if there is asymmetry in how single EA countries respond to the common monetary policy decided by the ECB. This is a vital question both from the ECB and from member states' perspective. Indeed, according to Barigozzi, Conti, and Luciani (2014), "the ECB has to take into account possible asymmetries in order to avoid instabilities within the EA, member states have to consider their reaction to the monetary policy before setting

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[3] See Jimborean and Mésonnier (2010).

appropriate national policies." For instance, one such issue could be related to price stability. Since its establishment, the ECB has defined price stability as its only objective, in terms of the average price developments weighted by the countries' relative household consumption expenditure shares. Hence, if inflation reactions remain weak in response to the monetary policy stance in larger countries compared to the responses in smaller ones, this would imply that the central bank would have to apply a stronger policy stance to bring average inflation back to target. Even in the latter case, pronounced differences in the responsiveness of output could imply an asymmetrical distribution of the burden of adjusting to EA-wide inflationary disequilibria (Mandler, Scharnagl, & Volz, 2016).

Also, the overall lending conditions are crucial to determine the level of economic activity and welfare. This is especially important in the case of the EA since bank loans represent approximately 50 percent of the external balance sheet financing for both small and large non-financial corporations (NFCs), accordingly making the EA vulnerable to the conditions of the banking systems.[4] The latter is also the primary reasons why we focus on the impact of monetary policy shock on credit institutions. If firms were to face working capital and wage constraints, any impairment of lending activities would deeply affect the hiring and investment decisions, and consequentially the economic activity. Impairments can either occur or be augmented by the ineffective pass-through or heterogeneity of the transmission of policy rate changes.[5] So far as the conduct of the monetary policy is concerned, it is worth pointing out that despite the single monetary policy being implemented to overcome the adverse effects of financial crisis and financial fragility, the system has so far proven to be largely inefficient. Many authors including Ciccarelli et al. (2013) already pointed to the possibility that the challenge for a major part lies in the EA banking sectors that hide a considerable degree of

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[4] While for a comparison in the US bank loans are only around 25 percent. See Altavilla, Canova, and Ciccarelli (2016).

[5] Since the early 2000s to the end of 2007, the monetary policy pass-through in the EA was relatively homogeneous across countries (see e.g. Ciccarelli et al. 2013) and almost complete in the long run (see Hristov, Hülsewig, and Wollmershäuser (2014)).

heterogeneity, regarding credit developments, the financial fragility of borrowers, lenders, and sovereigns and real activity.[6] While a small degree of national differentiation is considered a normal feature of a monetary union, the heterogeneity in economic conditions across EA states increased drastically in the aftermath of the crisis. Sufficient synchronization in business cycles and similar structure of sovereign states economic system remain two of the most fundamental requirements for an optimal currency area, pointing increasingly to possible repercussions to the homogeneity in the transmission of monetary policy. Many authors, including De Santis and Surico (2013) note that the response of bank lending to monetary conditions can vary across countries and that this difference might be especially significant within the banking sector, thereby making endogenously heterogeneous a common monetary policy. Other authors such as Barnes (2010) note that although earlier on financial integration and appropriate functioning of macro-financial linkages ensured that the monetary policy of the ECB would be transmitted homogeneously to the whole EA, the interconnections between market segments have largely broken, since the crisis.

"The most commonly used empirical methodology for studying monetary transmission, without using structural dynamic stochastic general equilibrium models, is based on vector autoregressive (VAR) models and the analysis of the effects of identified monetary policy shocks."[7] Hence, we also use a VAR approach. However, given the length and availability of the macroeconomic time series and in order to be able to include more than only two or three-time series we base our analysis on the work of B. S. Bernanke et al. (2005), Forni et al. (2009) and Blaes (2009).[8,9] Specifically, their utilization of factor models for forecasting applications

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[6] See Ciccarelli, Maddaloni, and Peydró (2013).

[7] See Mandler, Scharngal and Volz (2016, p.1).

[8] To see passible ways to overcome the problem of dimensionality in a structural VARs see also Banerjee, Marcellino, and Masten (2005), Forni, Giannone, Lippi, and Reichlin (2009) and Andreou et al. (2013).

[9] For forecasting applications see Stock and Watson (2002a), Stock and Watson (2002b) and Eickmeier and Ziegler (2008). While regarding structural analysis see, e.g., Baumeister, Liu, and Mumtaz (2010).

and structural analysis for testing the predictions of the macroeconomic theory. One major advantage of latter is to allow for dealing with very large panels of data without suffering from the problem of dimensionality. Also, by conditioning monetary policy on a large dataset, the FAVAR approach depicts a much more realistic model and thus, more accurate and precise estimates and impulse response functions. Accordingly, for a broader overview of the key issues associated with monetary policy transmission, it is then possible to analyze the evidence concerning the propagation mechanism of monetary policy on credit institution, monetary aggregates, government bond yields and financial sector equity prices, in more detail. We follow the methodology proposed by the authors, as we implement a FAVAR setup that we extend to explicitly include relevant fluctuations in the MFIs balance sheet items. One of the novelties of our approach in comparison to previous work is that we include netted positions through consolidation while being able to distinguish between the aggregated bank positions with other MFI and simultaneously control for their positions with the ECB. We perform the following, by relying on our use of a rich data set, which in our consideration was previously under-exploited. Such approach allows us to focus more directly on the evolution of quantities most immediately affected by monetary policy measures, rather than relying on the developments in interest rate spreads. In addition, as mentioned earlier, the EA financial system is mainly bank based and bank deposits and loans represent the bulk of financial intermediation, consequently they are particularly informative about the role of the financial sector in the transmission of shocks.[10]

Following the work of B. S. Bernanke et al. (2005), we test for heterogeneity in the responses across the four EA economies, after a standardized shock that corresponds to a 25 basis-point decrease in the ECB shadow rate. Moreover, after imposing a small set of restrictions on the response of a few selected indicators, we obtain the effects of monetary shocks and test the following hypothesis:

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[10] For instance, see Zentralbank(2009).

I.   **Hypothesis 1:** Transmission of monetary policy shocks is heterogeneous across Germany, Italy, Spain, and France for:

- Monetary Financial Institution Balance Sheet Items;
- Financial Sector Equity Prices;
- Monetary Aggregates;
- Long-Term Government Bond Yields.

II.   **Hypothesis 2:** Transmission of monetary policy shocks is heterogeneous across time for German, Italian, Spanish, and French:

- Monetary Financial Institution Balance Sheet Items;
- Financial Sector Equity Prices;
- Monetary Aggregates;
- Long-Term Government Bond Yields.

The master's thesis is structured as follows. In the next section, we briefly review the literature related to the transmission of monetary policy, credit channel view, development of the identification schemes and models for analysis of monetary policy shocks. We discuss the pitfalls of previously applied models, specifically the problems related to VAR analysis when compared to our FAVAR approach. In the second part, we then provide an in-depth overview of the methodology used along with data description and necessary adjustments of the latter. In the third part, we perform the empirical investigation of the impact of monetary policy shocks across countries and over time. Specifically, we study the question of heterogeneity in the effects of common monetary policy shocks on aggregate affect credit institutions across the four largest EA. Lastly, we briefly summarize our findings in concluding remarks.

2 Literature Review

In the decade preceding the global financial crisis, the predominant view of the monetary policy transmission mechanism was directed to the significance of the expectations channel of monetary policy. The latter influences output and prices exclusively through the expected path of future short-term rates.[11] By contrast, one of the consequences of the crisis was the revival of the credit channel view, according to which bank reactions in response to monetary policy decisions have a significant effect on the overall level of economic activity. It is fair to say that ever since the bankruptcy of Lehman Brothers, the relevance of the credit channel view was one of the most fiercely debated empirical topics in monetary economics.[12] This is a reoccurring phenomenon, since in previous cases of wide-ranging bank capital shortfalls, i.e. Japan in the late 1980s or the US in the early 1990s, empirical assessments for both bank and lending channel also gained considerable attention in academic and policy circles.[13]

Thus far two paths were followed in order to analyze the credit channel view. The first is based on a detailed set of individual bank information or bank level data, while the second relies on measures of aggregated credit levels. However, to date both methods remain fairly inconclusive in regard the macroeconomic importance of possible financial frictions. In this respect, we believe that our research will be more successful, as we follow the second approach in combination with the adoption of a rich data set, which we consider was previously underexploited: the monetary financial institutions (MFIs) balance sheet items for Germany, Italy, France, and Spain.

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[11] See, for instance, Blinder (1999), B. Bernanke (2004), and Woodford (2005).

[12] For a general perspective on the credit channel issue and usual distinction between the bank lending channel and the balance sheet channel of monetary policy transmission, see B. S. Bernanke and Gertler (1995). For a view of this debate at the EA level, see Angeloni, Kashyap, and Mojon (2003).

[13] See, e.g., Adrian and Shin (2009).

It is important to point out that the first strand of the literature emphasizes the aspect of micro-level data that should identify the role of bank heterogeneity and loan supply effects, by running a panel data regression on bank balance sheets to investigate the determinants of individual credit fluctuation (Ehrmann & Worms, 2001).The following study underlines the effect of several characteristics of banks, such as total assets, capitalization, and liquidity ratios in their response to monetary policy shocks. "It is typically the case for the traditional bank lending channel that monetary policy appears to be stronger for small, poorly capitalized and less liquid banks."[14] Having said that, a limit placed on the policy relevance on this segment of the literature is that there is little that could be determined from the results of micro-data studies regarding the relevance of bank heterogeneity from the macroeconomic perspective of monetary policymakers. In his work Ashcraft (2006) argues that from panel data regressions, one cannot infer on whether the financial frictions in the bank lending channel, which for instance affect small banks, do account for a significant portion of the decline in real economic activity that follows a monetary policy tightening.

The second strand of the literature relies on several other approaches in order to understand the propagation of monetary policy to the economy. Among others, dynamic stochastic general equilibrium (DSGE) models and structural vector autoregression (SVARs) are repeatedly used, with various degrees of success. For the DSGE literature, a representative paper is the one by Smets and Wouters (2005), who built on the previous work of Christiano, Eichenbaum, and Evans (2005), finding results comparable to the ones originating from empirical VARs. The authors made a remarkable contribution to the DSGE literature, as they built a model able to study monetary policy in an empirically plausible setup. More closely related to our empirical analysis, Peersman and Smets (2001) analyzed the responses of several financial and macroeconomic variables to a hawkish monetary policy disturbance while adopting a VAR approach. More recent papers include

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[14] See Jimborean and Mésonnier (2010).

Sousa and Zaghini (2007) and Weber, Gerke, and Worms (2009). The former analyzed the impact of monetary policy shock through SVAR approach, while the latter performed an area-wide study on monetary policy transmission within a VAR framework. Notably, this last part of the VAR literature follows B. S. Bernanke and Blinder (1992), by adopting a small monetary VAR at the macroeconomic level. Indeed, impulse response functions which the authors derive from structural VAR models that include a few macro variables (i.e., inflation and gross domestic product) provide an efficient tool for the evaluation of monetary policy transmission. Hence, by adding aggregated credit variables to the basic VAR framework, it should be relatively easy to assess the impact of monetary policy shocks on total credit and the importance of credit supply restrictions in economic downturns. In practice, however, it is not as straightforward.

According to B. S. Bernanke and Gertler (1995), the estimated response of total bank loans to monetary policy shocks appears to be muted and not significant. Upon a closer inspection into the dynamics of various aggregate bank credit series, i.e., loans to households versus non-financial firms', it is evident that this may result from a compensation effect of diverging responses of the main components in banks' loans portfolios (Den Haan, Sumner, & Yamashiro, 2007). Consequently, this hints that a small VAR model that includes only one or two credit variables is probably misspecified. A simple solution to this misspecification problem could then be to add several aggregated loan series. However, if we include additional variables in a VAR model the latter will be restricted by the degrees of freedom problem.[15] In addition, the information basis of a standard VARs that contains only a handful of macroeconomic and aggregated credit variables appears to be too narrow. Thus, the appropriate identification of credit supply effect remains out of reach. Moreover, by applying a simple VAR setup, it is not possible to distinguish between credit contractions following an interest rate hike. The following is either

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[15] We further analyze the following problem in the next subsection. Nevertheless, we note here that Giannone, Lenza, and Reichlin (2008) propose to overcome this dimensionality problem and estimate such a large-scale monetary VAR using Bayesian techniques.

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a consequence of banks facing deteriorating balance sheets and then rationing some borrowers within the process of deleveraging (loan supply effect) or a consequence of the deterioration of the outlook, which could potentially shift down the demand for bank lending (loan demand effect). Overall these limitations would suggest a practical strategy reliant upon the use of a data-rich environment à la Stock and Watson (2002a). A setup like the one proposed by these authors would more thoroughly exploit the information on heterogeneity in bank behavior and the way time affects changes. Accordingly, it seems more fitting to detect the potential active role of banks in the transmission mechanism of monetary policy shocks. Therefore, we follow B. S. Bernanke et al. (2005) and Blaes (2009) as we employ a FAVAR model. The latter is an extension of the VAR model, with the inclusion of factors reflecting all relevant credit fluctuations and representing a large enough data set, like the one followed by monetary regulators. A key characteristic of the proposed framework is that the extracts estimated from macroeconomic factors affect the data of interest by employing the information contained in a large set of economic indicators.[16]

Our work thematically fits with the abundant credit channel literature, yet, our interest in the study of heterogeneity in the transmission of monetary policy shock to the EA credit institutions is, to our knowledge, quite a novelty in the FAVAR literature. We are aware only of a few studies that go along vaguely similar paths. For instance, Gilchrist, Yankov, and Zakrajšek (2009) extract unobserved factors from a broad array of corporate bond spreads and analyze the economic effect of shocks to the measures of credit risk in a FAVAR model of the US economy. With a different identification scheme Boivin, Giannoni, and Stevanovic (2009) perform a similar exercise with credit shock that allows an economic interpretation of the principal component analysis factors. While the latter is close in spirit to our analysis, these studies do not deal directly with monetary policy transmission or heterogeneity. In addition, Dave, Dressler, and Zhang (2009) study the dynamic

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[16] A detailed description of the model and general assumptions can be found in section 3.2.

response of credit aggregates and bank-level loan growth measures to monetary policy shocks using disaggregated bank data for the US. They primarily focus on varied responses of different types of loans, similarly to Den Haan, Sumner, and Yamashiro (2007), however, they do not use their FAVAR model to assess whether there is a divergence or significant alternation in the transmission of monetary policy shocks regarding heterogeneity.

In a more recent paper, Cecioni and Neri (2011) investigate possible changes in the monetary transmission mechanism that might have affected the EA after the adoption of the single currency. The authors claim that estimations obtained with a structural, Bayesian VAR do not provide evidence of a significant change after 1999. Another methodological approach ties back to Barigozzi et al. (2014) who investigate asymmetries in the response of the Eurozone countries to a common monetary policy shock. A Structural Dynamic Factor Model is used to determine that individual countries exhibit heterogeneity in response to the ECB's decisions. Georgiadis (2015) tries to provide a plausible explanation to the asymmetries in the transmission mechanism, showing that a dominant part of the asymmetries across countries is explained by heterogeneity in financial structures, in labor market rigidities and differences in the industry mixture. Barigozzi et al. (2014) estimate a structural dynamic factor model for several EA countries over the period from 1983 to 2007. They compare the post- and pre-euro periods and according to them the monetary policy transmission mechanism has evolved towards more similar reactions, especially for output, yet marked differences remain between countries for inflation and unemployment. Additional studies that are also close to our research are Bagzibagli (2013) and Mandler et al. (2016), as both analyze cross-country differences in monetary policy transmission across France, Germany, Italy and Spain. In his work Bagzibagli adopts both a one-step and a two-step FAVAR approach to investigate the monetary transmission mechanism in the EA. The research explores the effects of monetary policy shocks on the entire EA, across countries and over time, while focusing on area-wide macroeconomic indicators. Similarly, Mandler et al. (2016) analyze the differences in transmission applying a Bayesian estimation approach.

A great part of the literature we cited is based on data preceding the euro, when EA members still had independent monetary policies (although to differing extents). Therefore, we note that the "differences in impulse responses to a monetary policy shock might either be a consequence of differences in the way a country's economy reacts to monetary policy (transmission mechanism in a narrow sense) or differences in the country's monetary policy reaction function, which describes how the national monetary policy endogenously reacts to shock-induced movements in variables."[17] In terms of our research and in order to draw any conclusions about heterogeneity, after the introduction of the euro, only the first element is relevant, as all four countries in our case have to be subject to an identical monetary policy reaction function. Accordingly, this would require to either focus on data after the introduction of the euro, or to carefully model the monetary policy reaction functions and the monetary policy shock.

2.1 Development of the FAVAR Model

Since the groundbreaking work of Sims (1980), vector autoregressive (VAR) models became a widely used scheme for analysis of monetary policy shocks and their effects on macroeconomic variables. Highlighted by B. S. Bernanke et al. (2005), these simple approaches, in general, provide plausible results, indicating the dynamic responses of main variables to monetary policy innovations, without a necessity to identify the entire macroeconomic model.

Despite all the advantages, standard VAR models do not lack for criticism. For instance, there is no consensus among researchers about the appropriate scheme for identifying monetary policy shocks. On top of that, another issue as already indicated in the previous section is that a VAR model only considers unanticipated changes in monetary policy. As highlighted by Sims and Zha (1998), most of the policy changes are systematic, and VAR models do not consider this systematic component. Consequently, the effect of monetary policy shock will be

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[17] See Mandler et al. (2016, p. 5)

underestimated. A series of additional critiques refer to the small size of data used by low-dimensional VARs. The latter includes only a reduced number of macroeconomic variables to preserve degrees of freedom. B. S. Bernanke et al. (2005) point out that six to eight variables at most are adopted in empirical studies. Central banks, on the contrary, follow an extensive set of information, which implies that it is necessary to consider the possibility that the results obtained can be biased, due to the omission of relevant variables. The discrepancy in information sets can generate statistically biased shock responses and economically counterintuitive results. For instance, the most typical illustration of this potential issue is the price "puzzle", explained by Sims (1992), when an unexpected monetary tightening leads to an increase in inflation in the impulse response function of the model, instead of a decrease as standard economic theory and empirical evidence would suggest.

With the purpose of resolving the issue with the use of VARs, B. S. Bernanke et al. (2005) introduced a way to adjust the analysis of monetary policy on richer information set, without losing the degrees of freedom in the model. They integrated the standard VAR analysis with factor analysis, wherein the small number of estimated factors is able to effectively summarize the information from a large number of time series. Specifically, in the newly formed FAVAR, the broad set of economic variables is assumed to generate a factor model in which a few common factors explain a major part of the variation and thus provide an exhaustive summary of the relevant information. According to the authors, the FAVAR framework allows for a better identification of the monetary policy shock compared to a standard VAR, since it explicitly accounts for the large information set that monetary regulators monitor in practice. Besides, it is not required to take an ex-ante approach on the appropriate measure of economic concepts such as real activity or inflation, as they are treated as common latent components. Finally, an additional feature which makes the FAVAR appealing is that the impulse response functions to a shock can be computed for any variable included in the data, while the dimensionality of the estimated VAR is kept low. This gives both more information

and provides a more comprehensive check on the empirical plausibility of the specification.

2.2 Identification of Monetary Policy Shock

We note that it is not because monetary policy shocks constitute an important source of business cycle fluctuations that we are interested in documenting the effects of such shocks. In fact, much of the empirical literature finds that monetary shocks contribute relatively little to business cycle fluctuations (e.g., Sims and Zha 2006). Instead, monetary policy affects importantly the economy through its systematic reaction to economic conditions. The impulse response functions to monetary policy shocks provide a useful description of the effects of a systematic monetary policy rule by tracing out the responses of various macroeconomic variables following a surprise interest rate change and assuming that policy is conducted subsequently according to that particular policy rule.

When it comes to the identification of monetary policy shocks, the latter is dealt in a considerable part of the literature, with no consensus among economists as to which method should be used to identify these shocks in a VAR framework. Different identification schemes imply several implications for the dynamic responses of the variables to the shocks. Christiano, Eichenbaum, and Evans (1999) introduced different identification methods to the existing literature and asserted that it was common to adopt the recursive hypothesis when identifying the monetary policy shock in the VAR models. The standard assumption in the proposed setup is for the shocks to be orthogonal to the information set used by the monetary authority. Furthermore, to classify the variables, a set of categorizations needs to be imposed. The first of three categories include variables that incorporate the information set of the monetary authority and respond to a policy with a delay of at least one-time period. The second category consists of the operational monetary policy instrument. The final category contains the variables that respond contemporaneously to the shocks. In addition, the authors proposed three identification schemes that provide benchmarking under the recursive hypothesis. In the first scheme, short-term interest rates are considered as the policy instrument.

This choice is based on institutional arguments. The second scheme employs bank reserves other than those acquired by loans as an operational tool. The justification of the use of the latter instrument was supported by the argument that changes in this variable mirror exogenous monetary policy shocks, without the intervention of money demand shock (Christiano & Eichenbaum, 1992). In the final scheme, the policy instrument is represented by the ratio of bank reserves, exclusive of those acquired by loans to total reserves. The use of this measure, introduced by Strongin (1995) is grounded on the argument that the demand for total reserves is entirely inelastic concerning short-term interest rates. This implies that a monetary policy shock initially alters only the total reserve composition.

Even though the recursive assumption is regularly followed, it has been criticized for limiting the existence of simultaneity when determining variables of the model. Therefore, some studies that apply structural VAR, forsake the assumption that the monetary authority considers only pre-set variables related to the monetary shock. When employing such approach, the isolation of the shock with OLS is no longer possible. Thereby, the introduction of additional restrictions is required. B. S. Bernanke et al. (2005) explain that some analysis impose either matrix restrictions, associated with the structural shocks to the VAR error, while others impose restrictions on a level of impulse response function for longer time horizons. As there is no consensus on which should be followed, matrix restrictions are often criticized for being arbitrary. Moreover, criticism addressed to long-term restrictions is concerning their inability to generate plausible results for short-term movements.

One of the above-mentioned critiques of the VAR model is that its framework considers only unanticipated changes in monetary policy. However, most policy changes are systematic, that is, they are responses to variations in the state of the economy. Thus, the effect of monetary policy shock is underestimated in VAR models. In light of this critique, it is significant to emphasize the source of the monetary policy shock.

As highlighted by Christiano et al. (1999), policy maker's systematic responses to variations in the state of the economy are usually determined with a reaction function. Nevertheless, not all alternations in central bank policy can be considered as a response to the state of the economy. "The unaccounted variation is formalized with the notion of a monetary policy shock."[18,19]

The most common economic interpretation of these policy shocks is a presence of measurement errors in the series used for decision making authorities (B. S. Bernanke & Mihov, 1995). To illustrate, we may define that monetary policy shocks arise as "errors of assessment of the economic situation"[20] by the central banks. Nonetheless, there are two additional interpretation of monetary policy shock. The first regards the monetary policy shock defined as a preference shift from the part of the monetary authority. Concurrently, the second argues that the monetary authority, tends to avoid the social costs of frustrating agent expectations and that a change in these expectations can lead to an exogenous shock.[21]

In our research, we will adopt the identification scheme proposed by B. S. Bernanke et al. (2005), which thoroughly described in section 3.4.2.2. Also, considering that we apply an interest rate as our policy instrument, it is important to consider the effects of the zero lower bound and the various alternative monetary measures. We describe the problematics associated with the latter and propose a solution in the following subsection.

2.2.1 Monetary Policy Shocks at the Zero Lower Bound

"Typically, to quantify the effects of monetary policy shocks, event study analysis building on Kuttner (2001) has been used."[22] The general assumption for such studies is that only monetary policy has an immediate impact on short-term interest

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[18] Christiano, Eichenbaum, and Evans (1999)

[19] See Appendix B for an algebraic representation of monetary policy shocks.

[20] See Uhlig (2005, p.398).

[21] E.g. see Chari, Christiano, and Eichenbaum (1998).

[22] Claus, Claus, and Krippner (2014).

rates. Correspondingly, then it is assumed that monetary policy shocks can be proxied by observable changes in a short-term market interest rate, on monetary policy event days. However, event study analysis is severely complicated by the binding zero lower bound. When short-term rates are at or near zero, authors argue that they can no longer proxy policy shocks. Otherwise stated, "with policy rates in the zero-lower bound range for a prolonged period of time, the practitioners have been put into a very awkward position of not being able to observe the actual stance of monetary policy."[23]

A solution to the mentioned problem is offered in the literature by the shadow short rate, which is obtained by modeling the term structure of the yield curve. According to Damjanović and Masten (2016), if we extract information from the yield curve, in particular, the level and the slope, could offer a summary of how monetary policy is perceived by the markets and what are the expectations of the future policy actions and the interest rates. However, a zero lower bound adjustment is required in such procedure, given that the yield curve modeling could broadly be described as summarizing the information from market interest rates at different maturities. This structure modeling has most notably been provided by the work of Krippner (2013, 2015) and Wu and Xia (2016). Also, based on the estimation of the latter, in our analysis, we will assume a standardized shock, which will correspond to a 25-basis-point increase in the ECB shadow rate.

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[23] Damjanović and Masten (2016).

3   Methodology

3.1   Factor Models

We begin by setting up the notation and making a distinction between a static and dynamic factor model, by following the procedure proposed by Bai and Ng (2008).[24] As the authors, we assume that a large number of informational background series are available, while they are observed for, $t = 1, 2, \dots T$ and denoted by the $N \times 1$ vector X_t. In this setup, we let N be the number of cross-section units and T be the number of time series observations. The dynamic factor model represents the observed series as a linear combination of two unobserved components: an idiosyncratic component and a common component, with the latter driven by factors. For $i = 1, \dots N, t = 1, \dots T$ a static model is defined as:

$$X_{it} = \lambda_i' F_t + e_{it} \tag{3.1.1}$$

$$X_{it} = C_{it} + e_{it} \tag{3.1.2}$$

where λ_i' is the factor loading, a vector of weights that unit i puts on the corresponding r static common factors F_t.[25] We can refer to the term $C_{it} = \lambda_i' F_t$ as the common component of the model and to e_{it} as the idiosyncratic error. For a better delineation, it should be taken into consideration on how factor models arise in economics. For instance, X_{it} is the GDP growth rate for country i in period t, F_t is a vector of common shocks, λ_i' is the heterogenous impact of the shocks, and e_{it} is the country specific growth rate. In finance, x_{it} is the return for asset i in period t, and F_t is vector of systematic risks (or factor returns) and λ_i' is the exposure to the factor risks, and e_{it} are the idiosyncratic returns. The main advantage of Bai and Ng's method is that their estimation results hold under weak serial and cross-section dependence in the idiosyncratic components. Therefore, we consider the model in equation 3.1.1 to have an approximate factor structure.

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[24] See Appendix C to see a more in-depth representation of factor models.
[25] See Bai and Ng (2008).

If we allow $X_t = (x_{1t}, \dots x_{Nt})'$, $F = (F_1, \dots F_N)'$ and $\Lambda = (\lambda_1, \dots, \lambda_N)'$, then our static representation of the model in vector form is:

$$X_t = \Lambda F_t + e_t \qquad (3.1.3)$$

By letting $X = (X_1', \dots X_N')$ be a $T \times N$ matrix observations, the matrix representation of the factor model is then:

$$X = F\Lambda' + e \qquad (3.1.4)$$

where $e = (e_1', \dots e_N')$ is a $T \times N$ matrix.

Even though the model specifies a relationship that is static between the observed variables and the factors, F_t itself can be a dynamic vector process that evolves according to $A(L)F_t = u_t$, where $A(L)$ is a polynomial (possibly of infinite order) of the lag operator. The idiosyncratic error e_{it} can also be a dynamic process, while the assumptions that follow also permit e_{it} to be cross-sectionally correlated.

The static model is to be contrasted with a dynamic factor model, defined as:

$$X_{it} = \lambda_i'(L)f_t + e_{it} \qquad (3.1.5)$$

Bai and Ng note that $\lambda_i'(L) = (1 - \lambda_{i1} L - \dots - \lambda_{is}L^s)$ is a vector of dynamic factor loading of order s. The term dynamic factor model is sometimes reserved for the case when s is finite, whereas a generalized dynamic factor model allows s to be infinite. In either case, the factors are assumed to evolve according to:

$$f_t = C(L)\varepsilon_t \qquad (3.1.6)$$

where ε_t are $i.i.d.$ errors. Based on the latter, we can make a first distinction between the static and dynamic representation of the dynamic factor model. From this point on, we will refer to the static term as the relationship between the common component and the variable that is static. Otherwise stated, in a static model the common shock affects all series contemporaneously. By contrast, when two or more different series are affected by different lags of the common shocks, the model will be called dynamic (Forni, Hallin, Lippi, & Reichlin, 2004).

In our analysis, we focus exclusively on factor estimation with static principal components. This decision was primarily based on Bai and Ng's conclusion that

although knowledge of the dynamic factors is necessary for some analysis, it turns out that many econometric methods can be developed within the static framework. The authors also establish that the properties of the static factors are much better understood from a theoretical standpoint, while empirically both approaches produce rather similar forecasts. From a practical perspective, the main benefit of the static framework is that it is easier to estimate using time domain methods and involves few choices of auxiliary parameters.

3.2   The FAVAR Model

Let us consider that Y_t is a $M \times 1$ vector of observable economic indicators assumed to drive the dynamics of the economy, and t to be a time index; t = 1, 2…, T. In like manner, let us suppose that additional information, which is not fully captured by Y_t, yet potentially relevant to model the dynamics of these time series, can be represented by a $K \times 1$ vector of factors, F_t, where K is "small". In accordance with B. S. Bernanke et al. (2005) we might think of the factors F_t, despite being a reflection of a wide range of economic variables, as a diffuse concept with no clear economic interpretation. It is additionally assumed that the joint dynamics of F_t and Y_t are described by a VAR system, providing the FAVAR model by B. S. Bernanke et al. (2005). We can summarize the FAVAR model in state-space representation as follows:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t, \qquad E(u_t' u_t) = Q \qquad (3.2.7)$$

Equation 3.2.7 represents the FAVAR model in (F_t, Y_t) and $\Phi(L)$ is a conformable lag polynomial of finite order d, and u_t is a $(K + M)$ column vector that $u_t \sim i.i.d.\,N(0, Q)$.[26]

Due to unobservability of the factors, F_t, equation 3.2.7 cannot be estimated directly. However, B. S. Bernanke et al. (2005) propose that unobserved factors can

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[26] Equation 3.2.7 is often referred to as the transition equation.

be extracted from informational time series included in $N \times 1$ vector of X_t.[27] The assumption is that the common dynamics of all variables in the economy, X_t, are driven by some "pervasive forces" and idiosyncratic components, while these forces are assumed to consist of both "unobservable" and "observable" parts. As already stated the variables that cannot be observed are summarized by the vector of factors, F_t, while the policy variable, i.e. federal funds rate or ECB's official refinancing operation rate, is assumed to be the only observable factor in the system. Accordingly, we may think of X_t as central banks' information set and of N as representing a large number, particularly N might be greater than the number of time periods T. X_t is also assumed to be much greater than the number of factors and observed indicators in FAVAR system (for concreteness, we assume $N > T$ and $N \gg K + M$). At the same time, the informational time series X_t is to be related to the unobservable factors F_t and observable indicators Y_t by the following observation equation:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \qquad E(e_t' e_t) = R \qquad (3.2.8)$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is $N \times M$, and e_t is an $N \times 1$ vector of mean-zero error and assumed to be either correlated or uncorrelated depending on the method of estimation of the model. Equation 3.2.8 captures the idea that both Y_t and F_t, represent common forces that drive the dynamics of X_t.[28] In addition, the error terms in equation 3.2.7 and 3.2.8 are presumed to be independent, while R is a diagonal matrix.

3.2.1 Impulse Response Function

One of the already mentioned advantages of the FAVAR methodology over a standard VAR approach is the ability to conduct impulse response analysis on a larger scale. Here we follow Blaes (2009) and explain how these functions are

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[27] We can interpret the factors as representing forces that potentially affect many economic variables, thus we may hope to infer about the factors from observations on a variety of economic time series (B. S. Bernanke et al., 2005).

[28] See B. S. Bernanke et al. (2005, p. 393)

obtained. The moving average representation of the transition equation 3.2.7, impulse response functions of $\widehat{F}_t$ and Y_t are given by:

$$\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \Psi(L)u_t \tag{3.2.9}$$

where $\Psi(L) = [I - \phi_1 L - \cdots - \phi_d L^d]^{-1} = [I - \Phi(L)]^{-1}$. Combining equations 3.2.8 and 3.2.9 leads us to the following transformation:

$$X_{it}^{IRF} = [\widehat{\Lambda^f} \quad \widehat{\Lambda^y}]\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = [\widehat{\Lambda^f} \quad \widehat{\Lambda^y}][\Psi(L)u_t] \tag{3.2.10}$$

which enables us to construct the impulse responses for any element X_{it} of X_t. It is important to specify that equation 3.2.16 exhibits the impulse response function to shocks, i.e. innovations in u_t. However, the main focus of the analysis is to study the responses of the variables of interest to structural shocks, such as monetary policy shock. As we describe in subsection 3.4,[29] it is necessary to identify the relationship between the reduced form and structural shocks for this purpose. The identification of the system allows us to calculate, in the same manner in equation 3.2.16, the responses of the variables in X_{it} to structural shocks.

3.3 Estimation

B. S. Bernanke et al. (2005) suggest two estimation procedures. The first is a one-step method, which employs Bayesian likelihood and Gibbs sampling techniques in the simultaneous estimation of the factors and the FAVAR model. The second is a two-step principal component approach, "which provides a non-parametric way of uncovering the space spanned by the factors of X_t."[30] B. S. Bernanke et al. (2005) emphasize that these approaches differ in various dimensions, nonetheless, there is no explicit a priori reason why one approach should be favored over the other. In virtue of its computational simplicity we thus opted for the two-step approach.

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[29] See subsection 3.4, part "Identification of the Monetary Policy Shocks" for details of the identification scheme employed in the chapter.

[30] See B.S. Bernanke et al. (2005, p.398).

3.3.1 Two-Step Principal Components Approach

The two-step principal component procedure estimates 3.2.7 and 3.2.8 separately. Parallel to the forecasting exercises of Stock and Watson (2002b), the first step of the procedure is applied to the observation equation 3.2.8 with an aim to estimate space spanned by the factors. For this purpose, the first $K + M$ principal components of X_t, denoted by $\hat{C}(F_t, Y_t)$, are used. Notice that the estimation of this step does not impose the constrain that the observed factors, Y_t, are among the common components. In other words, Y_t is separated from the space covered by the principal component by performing a transformation of the principal component acting upon the different behavior of the slow-moving and fast-moving variables, in the second step.[31] However, as highlighted by B. S. Bernanke et al. (2005), and presented by Stock and Watson (2002b), the principal components both consistently and regularly recover the space spanned by both F_t and Y_t. This will happen as long as N is large and the number of used principal components is at least as large as the true number of factors. The components are engaged in the first step of the procedure, with the intent to estimate factors $(\widehat{F_t^1}, \widehat{F_t^2}, \dots, \widehat{F_t^K})$ from the equation 3.2.8. Given the assumption of R being diagonal in 3.2.8, the approach employs OLS with the aim to obtain the estimates of factor weights $\left(\widehat{\Lambda_1^f}, \widehat{\Lambda_2^f}, \dots, \widehat{\Lambda_K^f}\right)$. In the second step, the unobserved factors in 3.2.8 are first replaced by their principal component estimates, and to obtain $\widehat{\Phi}(L)$, a standard VAR approach is imposed:

$$
\begin{bmatrix} \widehat{F_t^1} \\ \widehat{F_t^2} \\ \vdots \\ \widehat{F_t^K} \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \widehat{F_{t-1}^1} \\ \widehat{F_{t-1}^2} \\ \vdots \\ \widehat{F_{t-1}^K} \\ Y_{t-1} \end{bmatrix} + e_t \qquad (3.3.11)
$$

The main advantages of such an approach are the computational simplicity, ease of implementation, allowance of some degree of cross-correlation in the idiosyncratic

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[31] See Boivin, Giannoni, and Mojon (2008).

term e_t and that it imposes only a few distributional assumptions. Nevertheless, the approach implies the presence of generated repressors in the second step and thus necessitates the implementation of a bootstrap procedure that accounts for the uncertainty in the factor estimation. With the implementation, we obtain the accurate confidence intervals on the impulse response function.[32] Following the authors and the rest of the literature, our analysis employs the bootstrapping procedure proposed by Kilian (1998) to obtain confidence intervals on the impulse response functions.

3.4   Identification

In contrast to standard VARs, the identification of FAVARs is more complex. This is primarily because the model requires the identification of the factor spaces in addition to the identification of structural shocks. Moreover, since there is more than one structure of economic interest that can give rise to the statistical model for a vector of variables, some identification issue can arise (Favero, 2001). The proposed solution is to put identifying restrictions on the structure where the number of parameters exceeds that in the reduced form. In our empirical analysis, we follow the identification scheme and restriction implementation of B. S. Bernanke et al. (2005), discussed in the following subsections.

3.4.1   Identification of the Factors

There are two options for factor identification in FAVAR models. The first is to impose the restriction on the observation equation, while the second one is to restrict the transition equation.[33] B. S. Bernanke et al. (2005) prefer not to limit the VAR dynamics, but to impose restrictions on factors and their coefficients in observation equation. Accordingly, the best approach for factor identification in two-step estimation method is to either restrict loadings by $\frac{\left(\Lambda^f\right)'\left(\Lambda^f\right)}{N} = I$ or restrict the

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[32] See B. S. Bernanke et al. (2005, p.399).

[33] Regardless of the approach, both procedures provide the same common component $F\left(\Lambda^f\right)'$ and the same factor space. See Bernanke et.al (2005, p. 400-401) for a more detailed explanation.

factors by $\frac{F'F}{T} = I$. For the joint estimation, it is suggested to set the upper K x K block of Λ^f to an identity matrix and the top K x M block of Λ^y to zero. In other words, B. S. Bernanke et al. (2005) propose these restrictions for the purpose of normalizing or re-basing the factor space.

3.4.2 Identification of Monetary Policy Shock

We explain the problem of identification of a monetary policy shock in a FAVAR context first, then we summarize the identification schemes proposed by B.S. Bernanke et al. (2005) that we employ.[34]

"Since more than one structure of economic interest can give rise to the same statistical model for a vector of variables, the problem of identification arises."[35] In other words, it is impossible to draw a conclusion about the "true" model parameters from the data, since it is possible to obtain the same reduced-form from different structural models. It appears that the only solution to this issue comes from the imposition of identifying restrictions on the structure where the number of parameters is greater than that in the reduced form.[36]

Before going into detail about how the restrictions are imposed, we consider the reduced-form FAVAR equation 3.2.7:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t, \qquad E(u_t' u_t) = Q$$

Moreover, suppose an orthogonal and invertible matrix dimension $(K + M)$ x $(K + M)$, called A represents the contemporaneous relationship between the variables in the FAVAR model. Therefore, by multiplying the reduced form with A^{-1} the structural model can be acquired implying the following linear relation between the structural shocks (ε_t) and the reduced-form innovations (u_t):

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[34] For further details on the issue of identification in general see Favero (2001, Chapter 3 and 6) and Enders (2004, Chapter 5).

[35] See Favero (2001, p.85).

[36] See Bagzibagli (2013).

$$\varepsilon_t = A u_t \ \text{ or } \ u_t = A^{-1} \varepsilon_t \tag{3.4.12}$$

The moving average representation of the structural form, analogous to the equation 3.2.9 is given as:

$$\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \Psi^*(L) u_t \tag{3.4.13}$$

where $\Psi^*(L) = \Psi(L)A^{-1}$. Given these notations, one of the task of the analysis is to identify A or in our case only a row of A, as the aim is the identification of a single monetary policy shock. It is highlighted by Kilian (2012) that without a fitting identification of the underlying system, the analysis of the responses of variables in the FAVAR to reduced-form innovations will reveal nothing about that of the variables to the structural shocks. "It is the latter responses that are of interest, if we want to learn about the structure of the economy."[37]

According to B. S. Bernanke et al. (2005) and Kilian (2012), we can categorize the structural FAVAR models in the literature as identified by: (i) short-run restrictions, i.e. recursive, nonrecursive, and contemporaneous frameworks, (ii) long-run restrictions, (iii) sign restrictions, (iv) alternative approaches based on heteroscedasticity of the structural shocks, or high-frequency financial markets data, and (v) mixture of contemporaneous and long-run restrictions.[38]

We have already mentioned that our identification of monetary policy shocks would follow the scheme proposed by B. S. Bernanke et al. (2005). As shown by Stock and Watson (2005), it is possible to classify the latter into the category of contemporaneous timing restrictions, a brief explanation of which according to Stock and Watson, and Favero is provided.

3.4.2.1   Contemporaneous Timing Restrictions

Contemporaneous timing restrictions are exclusion restrictions, which state that certain structural shocks, such as monetary policy shocks or macroeconomic shock

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[37] Kilian (2012, p.3).

[38] Among others, see B. S. Bernanke and Blinder (1992) or Sims (1992).

do not affect certain variables, contemporaneously, within the quarter or the month depending on the frequency of the data. In his pioneering study, Sims (1980), proposed the following identification strategy for such VAR systems restrictions. This is based on Wold causal ordering of variables and Cholesky decomposition of the reduced form covariance matrix, i.e., Q in equation 3.2.7. Given the reduced-form of the FAVAR in equation 3.4.12, we assume that the orthogonal and invertible matrix of dimension $(K + M) \times (K + M)$, A, presents the contemporaneous relation between the variables in the FAVAR model.[39]

It is assumed by Sims (1980) that A is an invertible, lower triangular matrix as follows:

$$A = \begin{bmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ a_{N1} & \dots & a_{NN-1} & 1 \end{bmatrix} \qquad (3.4.14)$$

In the matrix, the a's denote unrestricted non-zero elements, while the lower triangular structure corresponds to recursive economic structure, with the most endogenous variable ordered last (Favero, 2001). In case we assume a FAVAR model with N variables, the lower triangular structure implies $N(N-1)/2$ exclusion restrictions in the matrix, implying that A is exactly identified.

It is common to assume that the shocks are orthogonal to each other and normalized to have a unit variance ($E[\varepsilon_t \varepsilon_t'] = I$). In view of the relation between the reduce-form innovations and the structural shocks in 3.4.12, the covariance matrix of the former can be reformulated by following procedure:

$$Q_u = E[u_t u_t'] = A^{-1}, \qquad E[\varepsilon_t \varepsilon_t'] A^{-1'} = A^{-1} A^{-1'} \qquad (3.4.15)$$

Stock and Watson (2005), among others, proposed Cholesky decomposition of the covariance matrix Q_u as a credible solution for retrieval of ε_t and thereby for the precise identification of the system. The decomposition is applied in the following

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[39] According to Favero (2001, Chapter 6), this is the main assumption separating the traditional Cowles Commission and the VAR models as identification in the former models is obtained without assuming orthogonality of the structural disturbances.

manner: when $A^{-1} = S$ where S is the Cholesky decomposition of the covariance matrix Q_u, such that $SS' = Q_u$, the lower triangular structure of S provides $N(N - 1)/2$ free parameters as in 3.4.12.

In the second example of contemporaneous timing restrictions, Stock and Watson (2005) propose the identification scheme of Bernanke, Boivin, and Eliasz as "partial identification via block lower-triangular exclusion restrictions" (p.18). The following is also the scheme that we employ in our empirical work.

3.4.2.2   Bernanke, Boivin and Eliasz Identification Scheme

To identify a single shock in structural FAVAR model, B. S. Bernanke et al. (2005) introduced a scheme in which they divide the structural shock and X_{it} into three groups: "fast-moving" variables, "slow-moving" variables and the monetary policy variable. While "fast-moving" variables are characterized as highly sensitive to contemporaneous economic news or shocks, the "slow-moving" ones are assumed to be largely predetermined as of the current period. Examples of "slow-moving" variables include output, employment, and price series, while "fast-moving" variables include interest and exchange rates as well as monetary aggregates.[40]

Given the above-described decomposition, B. S. Bernanke et al. (2005) propose that a standard recursive structure should be used for the transition equation 3.2.7 to identify the monetary policy shock. Ordering policy instrument last after the "slow-moving" factors, performs this. The underlying identification assumption is that the slow-moving variables do not respond contemporaneously to changes in policy variable. In contrast, the "fast-moving" variables are presumed to develop closely with the movement of the monetary policy instrument. In the aim of preventing the collinearity in the structure, the authors eliminate these factors from their recursive structure.

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[40] See B. S. Bernanke et al. (2005) for a more detailed explanation of the criteria used to classify the variables.

To show the scheme algebraically,[41] we have Ψ_0^* as the coefficient matrix, which is the leading zero-lag term of $\Psi^*(L)$ in equation 3.3.19. In addition, it is supposed that the structural shocks are $\varsigma_t = (\varsigma_t^{S\prime}, \varsigma_t^R)\prime$, where R is the policy variable, S stands for the slow-moving $\varsigma_t^{S\prime}$, is K_s x 1, and ς_t^R is a scalar. In the previous section, we explained the contemporaneous timing restriction that leads to the following block lower triangular structure for Ψ_0^*:[42]

$$\Psi_0^* = \begin{bmatrix} \Psi_{0,SS}^* & 0 \\ \Psi_{0,RS}^* & \Psi_{0,RR}^* \end{bmatrix} \qquad (3.4.16)$$

where $\Psi_{0,SS}^*$ is $K_s \, x \, q_s$, $\Psi_{0,RS}^*$ is $1 \, x \, q_s$, and $\Psi_{0,RR}^*$ is a scalar. Following Stock and Watson (2005), the block restrictions expressed in equation 3.4.16 identify the shock of interest ς_t^R, and the space spanned by ς_t^S. According to the authors "the identification of ς_t^R means that the column of $[\Psi^*(L)]$, which is associated with ς_t^R is also identified and thus the structural impulse response of X_t with respect to ς_t^R is identified".[43]

Two-step FAVAR. To implement the form in the two-step FAVAR model, further adjustments, are needed. To regulate the part of the space spanned by the factors, i.e. $\hat{C}(F_t, Y_t)$, corresponding to the monetary policy variable Y_t, B. S. Bernanke et al. (2005) propose the following procedure: First, slow-moving factors, F_t^s, as the first K principal components of the "slow-moving" variables in X_t need to be estimated. Second, by estimating the following regression:

$$\hat{C}_t = \beta_{F^s}\widehat{F_t^s} + \beta_Y Y_t + e_t \qquad (3.4.17)$$

we construct $\hat{F}_t$ from $\hat{C}_t - \widehat{\beta_Y}Y_t$. Note that as $\widehat{F_t^s}$ and Y_t are correlated, so are $\hat{F}_t$ and Y_t. Finally, the FAVAR in $\hat{F}_t$ and Y_t can be estimated and the monetary policy shock identified recursively using this ordering.

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[41] See Stock and Watson (2005, p. 18-20) for further details of this part.

[42] Stock and Watson (2005) includes the "fast" variables in this expression, yet due to our explanation of the scheme above, these variables are excluded here.

[43] See Stock and Watson (2005, p. 18)

3.5   Country-Level and Panel Approaches

As represented in the previous subsection, we use the two-step technique for the estimation of our FAVAR model. The factors that are used in the transition equation (3.2.8) of the model can be obtained in two manners. Firstly, we can use a country estimation approach and thus estimate the shocks by extracting the country-level factors from the individual data sets, for each country under investigation. That is to say, we can construct a country-level X_t^{CL}, from which we extract the factors and use them in the transition equation (3.2.8) of our FAVAR model.[44] Technical representation of the estimation is as follows:

$$X_{it}^{CL} = \Lambda_i^{f^{CL}} F_t^{CL} + \Lambda_i^{y^{CL}} Y_t^{CL} + e_t^{CL} \qquad (3.5.18)$$

$$\begin{bmatrix} \widehat{F}_t^{CL} \\ Y_t \end{bmatrix} = \Phi^{CL}(L) \begin{bmatrix} \widehat{F}_{t-1}^{CL} \\ Y_{t-1} \end{bmatrix} + u_t^{CL} \qquad (3.5.19)$$

where $X_{it}^{CL(j)}$ contains country specific variables ($i = 1,2,\dots,n$), $t = (1,2,\dots,t)$ and $j = $ (Germany, Spain, Italy, and France). Secondly, when joining country-level variables into a balanced area-wide panel, we can acquire the area-wide factors. More precisely, while applying the two-step estimation approach, all 366 variables are combined in a single X_t^{AW} as shown in the following state-space representations:

$$X_{it}^{AW} = \Lambda_i^{f^{AW}} F_t^{CL} + \Lambda_i^{y^{AW}} Y_t^{AW} + e_t^{AW} \qquad (3.5.20)$$

$$\begin{bmatrix} \widehat{F}_t^{AW} \\ Y_t \end{bmatrix} = \Phi^{AW}(L) \begin{bmatrix} \widehat{F}_{t-1}^{AW} \\ Y_{t-1} \end{bmatrix} + u_t^{AW} \qquad (3.5.21)$$

In order to minimize possible cross-country heterogeneity in the monetary policy shock, we rather base our estimates on the area-wide approach. The main reason is that, since significant differences exist in the economic structure of the four countries, the estimated factors in a country-level approach will give rise to different country specific sequences of monetary policy shocks. Therefore, for each

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[44] See equation 3.5.18 below.

country-level FAVAR, factors will be different and the identified shock will thus be different, making the responses incomparable. Consequently, to avoid the problem of heterogeneity in identification of the shocks, we rather combine all country-level variables into a balanced panel to obtain the area-wide factors.

4   Preliminary Analysis

After explaining the methodological approach, the following subparts contain the list of preliminary work necessary prior to estimating the empirical results that are presented in Section 5. First, we explain the data with all the appropriate adjustments, while in the second and third step we report how the number of factors and lags are determined. Correspondingly, we also develop a discussion in regard to the reasons behind our estimation techniques and compare our procedure with previous work.

4.1   Data

The data set analyzed in the chapter is a balanced panel of 367 monthly series for the German, French, Spanish and Italian economy, which spans over the period from 2004:9-2016:12.[45] Following the FAVAR literature, our time series contains macroeconomic indicators along with balance sheet items pertaining to MFIs. In this regard, the first part of the variables, i.e. the macroeconomic, is very similar to those used by Stock and Watson (2002) and Bernanke, Boivin, and Eliasz (2005). The data were mainly sourced from Eurostat and Statistical Data Warehouse, as the latter publishes subsections of aggregated MFIs balance sheets items, similarly as Eurostat keeps a collection of macroeconomic variables of the European Union states, dating back to the 1990s.[46] This provided us with a collection of consistent price and volume data over an extended period of time. The following economic

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[45] The beginning of the sample is restricted by the availability of observations for MFIs balance sheet items and the European Central Bank shadow rate. For the first the observations start in January 2003, while the second start in September 2004. Considering that our main interest lies in the post crisis period and that 12 years of observations still provide a period long enough to ensure consistent results, we then opted for September 2004 as the start of our observation period.

[46] A detailed description of MFIs balance sheet items can be found in the following subsection.

categories were included in our empirical research: industrial production, inflation, retail sales and turnover, employment, exchange rates, long-term interest rates, share price indices, money and credit aggregates, confidence indicators, and some "foreign" variables such as prices, interest rates and stock markets for Japan, Switzerland, US and UK used as proxies for external real, nominal and monetary nuance's. In the aim to capture the movements of the financial sector's equity prices, we use a MSCI financials index. With all securities in the index classified in the financial sector, the index is designed to measure the performance of the large and mid-cap segments of countries' equity universe.[47] For a more detailed description of the series, data transformations and sources see Appendix A.

Also, we highlight that for the assessment of monetary policy actions, FAVAR models require the use of high-frequency data collected on a large set of macroeconomic time series. Thus, in favor of the best measure of the impact of monetary policy shocks, we opted for a monthly level time series. We promote the adoption of monthly over quarterly data, as a balanced quarterly panel from 2004:9-2016:12 may not have enough observations to ensure precise estimation. Most commonly authors adopt the same level of data frequencies for the estimation of FAVAR models. For instance, B. S. Bernanke et al. (2005), among others, evaluate a monetary policy in a FAVAR framework adopting only monthly variables. However, despite the popular approach, this estimation method discards potentially significant variables that can only be observed at other than monthly frequencies. In order to illustrate, a monthly data approach leaves out real GDP, which is commonly accepted as the most accurate measure of economic activity. One possible solution is to aggregate monthly variables to a quarterly level and estimate the model on a quarterly frequency. However, the quarterly model is subject to an

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[47] For a more detailed description of construction and calculation methodology of the MSCI financials indices, see MSCI Index calculation methodology (2017).

aggregation bias, which implies that valuable information gets lost in the aggregation process.[48] The data are processed as follows:

Firstly, some macroeconomic series showed periodic fluctuations, and, thus necessitated seasonal adjustments. This was performed by using the X-12-ARIMA program published by US Census Bureau. It is important to note that financial variables such as stock prices, exchange rates, and interest rates were not seasonally adjusted, as we do not believe they have seasonal patterns.

In the second step, we used McCracken's package developed in collaboration with the Federal Reserve to correct the series for significant outliers.[49] The transformed seasonally adjusted series were screened for outliers exceeding ten times the interquartile range, and all the outlying observations were replaced by the linear interpolation of neighboring, non-missing values.

Lastly, as shown in Appendix A, the data are transformed to induce stationarity.[50] First differences of logarithms are applied on all non-negative series that are not already expressed as rates or percentage units, as no changes had been implemented to the latter. Moreover, we adopted the same type of transformation for all variables in the same category (e.g., first differences of logarithm were taken for all industrial production indices).

4.1.1 Monetary Financial Institutions

Loans, debt securities, deposits liabilities and monetary aggregates have a long history of association with central banks and have at times occupied a central position in the conduct of monetary policy. Some central banks, most notably the ECB, still emphasize monetary policy effects on the latter, especially after the initial

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[48] Also, we would want to add that by including a small number of quarterly series would not affect the number of static factors needed to model the economy. More so because the quarterly variables can be explained with corresponding monthly variables (i.e. quarterly GDP can be explained with the factor closely related to the monthly variables that represent economic activity and the GDP deflator to the factor that predominantly explains monthly prices.).

[49] We would want to thank the author of the code, Michael W. McCracken, for making the program publicly available on the Federal Reserve Bank of St. Louis site.

[50] See B. S. Bernanke et al. (2005) and Bagzibagli (2013).

stages of the financial crisis. Of course, great understanding is needed from central banks in terms of these series, as they offer "an important insight on how to identify the buildup of future imbalances and potential transmission of financial shocks."[51] Many authors, including Kim, Shin, and Yun (2013) highlight other motives why dynamics of monetary aggregates should be thoroughly researched. The latter concluded that monitoring developments in monetary aggregates can provide an early warning signal of risks to financial stability. In another study, focused on bank liabilities, Hahm, Shin, and Shin (2013) show that increases in non-core bank liabilities indicate greater vulnerability to currency and credit crises, which according to the authors is an indicator with a greater predictive power than the credit-to-GDP ratio.[52]

Considering all the underlying factors, we thus believe that the ECB's framework of monetary analysis is a useful starting point for detailing the monetary transmission in the EA.[53] A distinctive feature of this framework is the structure of the balance sheets of EA MFIs, which is decomposed into assets and liabilities. As already mentioned, all the information relative to the data can be found on the Statistical Data Warehouse site, which reports all series based on a residency principle that covers all the subsidiaries and branches of banks located in an economy, irrespective of the nationality of their parent bank. Therefore, their balance sheet information is reported in respect of their resident offices only, which implies that intra-group positions and transactions are captured in these data (i.e., the extra-euro area assets of an EA bank can reflect its claims on another bank subsidiary within its banking group located outside the EA). The latter is one of the

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[51] See Everett (2016, p.2).

[52] Non-core bank liabilities are categorized as those not included in core liabilities and defined as retail deposits (they display relatively greater procyclicality).

[53] In the EA, monetary analysis is conducted on MFIs which are money-issuing entities including banks (termed credit institutions), money market funds and the Eurosystem of Central Banks. To avoid methodological and empirical issues related to the complex transactions between banks, money market funds and the Eurosystem, the focus of this paper is on EA banks. In the context of the stylized framework and empirical analysis presented in this paper banks represent MFIs. A detailed description of the construction of EA bank balance sheets can be found in the ECB's Manual on MFIs Balance Sheet Statistics, 2012.

most attractive characteristics of the data set, as it allows a researcher to focus exclusively on specific aggregated asset or liability item dynamics within the chosen country, i.e. loans to households. Accordingly, then all the MFI data series that we use for the aforementioned economies, have domestic series as the counterparty area implying that, i.e. all loans to households on aggregate reports only the loans issued to households within a country by domestic MFI.[54] We opted for the latter, because we believe they better capture the transmission of monetary policy in the respective economies.

In a sense, it is possible to partially recreate these aggregated series from bank balance sheet information, and it is also the case that by doing so the data set can be separated into much broader categories than MFI data allow for (i.e. the aggregated loan series could be separated into two categories, one for small banks and one for large banks). However, by doing so we would face two major issues. First, we would not be able to aggregate based on a residency principle, as banks reporting system differ majorly from country to country. Second, we would need to change our data frequency from monthly to quarterly, as all bank-level balance sheet items are only reported in quarterly frequencies, which would drastically shorten our post-crisis observations and hamper our estimation.

4.2   Estimating the Number of Factors

"Some economic models have a natural role for factors and thus determining the number of factors is an interest in its own right."[55] For instance, underlying the arbitrage pricing theory of Ross (1976) lies the assumption that there are common risk factors across assets, while on the other hand, the consumer demand analysis is of the notion that there are individual factors common across goods. In this regard, a wide range of studies from Lewbel (1991) to Bai and Ng (2008) propose

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[54] It was possible for us to choose from the following counterparty areas: EA, other EA member state and domestic. The only variable that was not available for the domestic counterparty area were total Asset/Liabilities, hence we instead used the EA data. See also Statistical Data Warehouse for more information.

[55] See Bai and Ng (2008, p. 14).

different estimation techniques to determine the number of factors in large dimensional models. The mentioned Lewbel (1991) along with Donald (1997) test for the number of factors using matrix ranks, while authors such as Forni and Reichlin (1998) suggested a different, graphical, approach to the problem. Stock and Watson (1998) showed that a modified Bayesian information criterion (BIC) could be used to determine the optimal number of factors for forecasting a single series.[56] However, as claimed by B. S. Bernanke et al. (2005) the most commonly used approach remains the study conducted by Bai and Ng (2002). The authors developed a class of estimation for the number of static factors k, which is motivated by the information criteria used in model selection. These criteria are set to determine the tradeoff between including additional factors and the cost of increased variability, due to the addition of parameters. From a statistical standpoint, being able to determine the number of factors consistently allows the researcher to treat k as known. Thus, it is possible to simply deal with the K x 1 vector of factor estimates $\widehat{F}_t$, instead of a sequence of factor estimates $\widehat{F}_t^k$. Bai and Ng treated this as a model selection problem and suggested an approach that can "consistently" estimate the number of factors when both N and T simultaneously converge to infinity.[57] It is nevertheless true that B. S. Bernanke et al. (2005) also point out that the commonly used Bai and Ng's (2002) criterion "does not necessarily address the question of how many factors should be included in the VAR."

It is important to stress that the above discussion and our results focus on static factors only, as already discussed at the end of section 4.1. The dynamic factors have taken an important place in the monetary literature in the form of dynamic principal components, but B. S. Bernanke et al. (2005) notes that based on the work of Stock and Watson (1998) we can interpret static factors, i.e. F_t in the measurement equation 3.2.8, as including arbitrarily lags of the fundamental

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[56] In addition, see Forni et al. (2000) where a multivariate variant of the Akaike information criterion (AIC) is used.

[57] See Bain and Ng (2008).

factors. Consequently, it is possible to consider the model as if it was indirectly allowing for dynamic factors.

For us to determine the number of static factors, we follow a two-step process. Firstly, we test the number of static factors in our data using (i) all the panel and information criteria proposed by Bai and Ng (2002), and (ii) we use the Bayesian information criteria (BIC) as a checking method. According to our tests, on the one hand, when we allow a maximum of 10 factors in the estimations our Bai and Ng (2002) approach suggests 10 factors. Whereas, our BIC criterion also estimates 10 factors as optimal.[58]

Secondly, as can be seen in Figure 1 we estimate the R^2 statistic measuring the proportion of the total variation in the variables explained by that in the common components of the model. In other words, R^2 is the explanatory power of $\widehat{\Lambda^f}\,\widehat{F}_t +$ $\widehat{\Lambda^y}Y_t$ in the observation equation 3.2.8. The following is computed for all 366 variables in the data set. Figure 1 presents, our findings that having 10 factors (Bai and Ng (2002) and BIC) instead of 5 only brings a marginal gain of less than 5 percent.
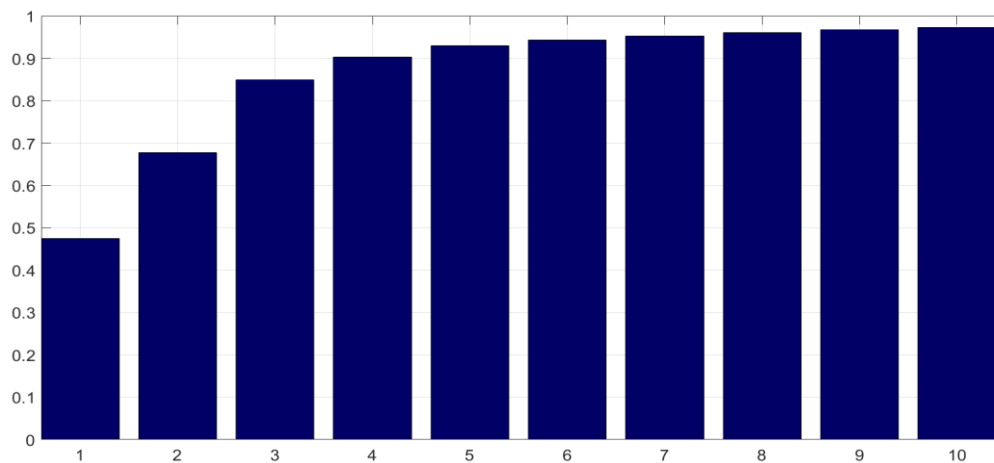

Figure 1: Number of Factors: R^2 Statistics - All Variables

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[58] We would like to thank Christophe Hurlin for making publicly available Bai and Ng's (2002) code, for determining the number of factors in approximate factors models.

Therefore, given that 5 factors in our data set account for more than 90 percent of the variations of the whole data set, we prefer to keep dimensionality low and use "only" 5 factors in our empirical analysis.[59]

4.3   Estimating the Number of Lags

Similarly, to the problem related to the choice of the appropriate number of factors, the lag length of the transition equation is an additional specification that needs to be determined. The importance of the specification of the number of lags was demonstrated by Braun and Mittnik (1993), who show that the estimated impulse response functions and variance decompositions obtained from a VAR are inconsistent when the specified lag length does not equal the actual lag length. Lütkepohl (2005) adds to the literature by indicating that while over-fitting a VAR model causes an increase in the mean-square forecast errors, under-fitting the lag length in most cases generates autocorrelated errors.

In the VAR literature, lag lengths are frequently selected by using statistical criteria such as AIC, final prediction error (FPE), Schwarz and Hannan-Quinn (HQ),[60] yet there is no a priori criterion that would perfectly estimate the number of lags in a FAVAR model. To illustrate, several authors adopt a different number of lags, among other B. S. Bernanke et al. (2005) and Belvisio and Milani (2006) use 13 lags to allow for sufficient dynamics, while Stock and Watson (2005) adopt 2 lags in their updated version of Stock and Watson (2002b) data set.

For us to select the optimal number of lags, we follow Bagzibagli (2013) and replicate a FAVAR by extracting five "slow moving" static factors, while we treat the ECB's shadow rate as the only factor that can be observed in the model. Then, by using the JMulti v-4.24 program,[61] we test for the lag length with all the selection criteria listed above. The general results suggest that: we should use 3 lags based

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[59] Previous work from, i.e. Eickmeier and Breitung (2006) or Altissimo, Benigno, and Palenzuela (2011) partially supports our estimations results.

[60] See Bagzibagli (2013, p.37-38).

[61] For software details see Lütkepohl and Krätzig (2004).

on our AIC results, with the FPE we should use 2 lags, while both the HQ and Schwarz criterion also suggest the adoption of 2 lags. It can be clearly seen that only a few number of lags, i.e., 2 or 3, are enough to describe the variation of our data set properly.

Given the fact that we only have a short period encompassing 12 years of data, and also given the results obtained by the selection criteria, we prefer to be as parsimonious as possible and adopt "only" 2 lags in our empirical estimation.

5   Results

In this section, we move to the empirical findings of the interactions between monetary policy and economic variables using the described FAVAR model. To examine the effects of monetary policy shocks, we follow the approach applied by B. S. Bernanke et al. (2005) and we estimate a single FAVAR model combining four country-level data sets and "foreign" variables.[62] As previously stated, our objective is to both clarify how a monetary policy shock affect the financial markets, highlight possible time-varying distributions and most importantly determine, if there is significant heterogeneity in the transmission of a single shock across the four countries. The comparison is based on the impulse response functions of 16 variables to a 25-basis-point contractionary monetary policy shock. Also, in section 5.2 we use a rolling windows approach to study the changes, if there are any, in the impact of the shock across countries over time and especially due to the financial and sovereign debt crisis.

Our main results for the four economies are presented in Figure 2 for our panel estimation and from Figure 7 to 11 for our time variation approach, while the results for both parts can be found in Appendix D and Appendix E, respectively. Further, we present our results for the key variables with 68% confidence intervals in

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[62] To have a better overview of "foreign" variables it is recommended to either see section 4.1 or Appendix A.

response to a contractionary monetary policy shock.[63] However, for the sake of comparability of the impulse response plots, we exclude the bootstrapped confidence bands for the Italian, Spanish and French series from Figure 2, instead we present them separately in Figures 3 to 6.[64] Then in order to have an approximate measure of asymmetries for both the panel and time variation approach, we rely on a simple procedure with a clearly intuitive meaning. In Figure 2 and from Figure 7 to 11 we keep the confidence intervals for Germany, as they help us determine whether the impulse responses are heterogeneous. In each plot the dashed lines represent the estimated 68% confidence interval for Germany. If at horizon h the impulse responses are contained within the confidence bands, it means that the impulse response of a given country and that of a benchmark country, i.e. Germany, are not different at horizon h.[65] A similar procedure is used also by Fielding and Shields (2011). Moreover, the impulse response functions are reported for a period of 48 months after the initial shock and, as explained above, our FAVAR model is estimated with 5 factors and 2 lags, while all the estimation results are expressed in standard deviation units. For the purpose of this research, in the first part when we refer to statistical significance, we refer to the latter in terms of the 48-month horizon and not in terms of heterogeneity among countries.

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[63] Note that it is quite common in the monetary literature, based on the FAVAR models to set the confidence bands to 68%, see e.g. Lagana and Mountford (2005), Belviso and Milani (2006), Boivin and Giannoni (2008), or Mandler et al. (2016). At the same time, in their original work B. S. Bernanke et al. (2005) on the other hand use 90% confidence intervals.

[64] At the same time, we do not present the confidence intervals for our time variation approach.

[65] Ever since its establishment, the ECB worked on maintaining relative price stability mainly through inflation targeting. However, the diversity among the member states in the EU and the EA requires not only collective attention on the EU economy but also on each individual member state. Some EA member states experience generally higher levels of inflation and higher unemployment. On the other side are countries like Germany which are more concerned with maintaining low inflation only. The literature on the topic suggests a theory known as the German Dominance Hypothesis (GDH), which explains the prevailing role of Germany and German's economic objectives on the ECB decision-making process. The ECB has also even been named "twin sister of the Bundesbank" mostly because it was initially modeled on the German central bank (Debrun, 2001). Although the theory provides mixed results on the matter, there is no doubt that Germany in terms of its voting rights and its economic influence has the greatest impact on the monetary policy in the EA. Accordingly, we believe that it is then fair to measure heterogeneity only in comparison to the German economy. Although, there might be a significant difference in terms of heterogeneity in the periphery of the EA, policy settings are unlikely to change, if the country with most influence is operating at what the country authorities consider an optimal level.

5.1 Baseline Result

Broadly speaking, the estimated monetary transmission mechanism in Figure 2 are largely consistent with economic theory following a contractionary monetary policy shock, government bond yields first increase and then they gradually decline, financial indices decline and for a major part so do the loan series. In addition, one can immediately notice the distinctions in the effects of a monetary policy shock in the EA, as in a general way they appear to be different among the four economies. After a monetary contraction, we estimate that part of deposit liabilities, all monetary aggregates, and a majority of lending series have responses that are heterogeneous. At the same time, if we observe debt securities held, financial indices and deposit liabilities for non-MFIs, we find that they move in tandem. The impulse response functions also display some price "puzzles".[66] In such context, we emphasize the word "puzzle" as we believe that these responses, which are contradictory to the general economic theory, might as well be a noteworthy sign of substantial differences among countries. The details of the results are as follows.

Contribution to Monetary Aggregates. Let us start with the analysis of broader monetary aggregates and their components, since they help us understand the behavior of bank liabilities over the business cycle, but also because the ECB pays particular attention to M3 under the second pillar of its monetary policy strategy.[67] We note that inconsistent with Blaes (2009) for the EA, the responses of the contributions to "narrow money" M1 are statistically significant for all countries, while only the German response shows statistical insignificance throughout the

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[66] Recall from the section "Development of the FAVAR model" the most typical illustration of the issue of price puzzle, explained by Sims (1992), is when an unexpected monetary tightening leads to an increase in the impulse response function of the variable, i.e. inflation, while economic theory and empirical evidence would instead suggest a decrease.

[67] To reach the target of price stability in a way which allows the realization of other macroeconomic targets as far as possible the ECB needs a "navigation system". Therefore, it helps to identify whether the main target and the other targets can be reached at a given policy stance or whether a more restrictive or more expansionary course of monetary policy is required. At the level of intermediate targets, the ECB has decided to assign a "prominent role" to money by using the money stock M3 as a "reference value" for its monetary policy. The second pillar of its the strategy is a "broadly based assessment of the outlook of price developments."

entire horizon. To the extent of our knowledge, no clear explanation on the issue of statistical insignificance is provided in the FAVAR literature. When it comes to the impacts of common monetary tightening, monetary aggregate M1 very importantly displays one of the most heterogeneous responses across the four EA economies. Among the indicators presented in Figure 2, only the German impulse response function remains within the confidence bands, signaling that there are significant differences in "narrow money" creation among countries. Our point estimates suggest, that where there is a hike in the interest rate due to the shock, M1 unsurprisingly responds negatively for all economies, before showing a reversal in the case of Germany. That said in Italy, France, and Spain the fall is immediate and persistent. These results are theoretically consistent with a typical IS-LM model of an open economy and are commonly accepted in the literature (Barigozzi et al., 2014).

Second, in the response of the country contribution to money aggregate M3, consequent to a one-off monetary policy shock, we see M3 falling for both Italy and Spain. By contrast, the response for Germany and France is positive at first, then after approximately 10 months, we observe a reversal followed by a persistent decline. According to Blaes (2009), "the initial positive response of the nominal M3 to monetary tightening can be explained by temporary portfolio shifts: higher short-term interest rates at first render the short-term assets contained in M3 more attractive than longer-term investments, leading to a temporary increase in money stock M3" (p.11). However, it is true that in his work Blaes focuses on the period before the financial crisis. Thus, we believe that there are additional factors that could possibly explain such dynamics, among others, the historically low-interest rate levels, the flat yield curve and the heightened political and economic uncertainty that persisted in the aftermath of 2008. These factors cause agents to make large scale shifts in their portfolios in favor of highly liquid safer investments, i.e., cash, short-term savings deposits and, above all, sight deposits for German banks. "Given the particularly low-interest rate spread in Germany, between sight deposits on the one hand and short-term time deposits and savings deposits on the other, it was mainly sight deposits that benefited from investors' increased

preference for liquidity."[68] With risk aversion still high and considering the ongoing low level of opportunity costs compared with longer-term deposits, investors supposedly prefer to hold large shares of short-term deposits in their portfolios, even though it results in accepting a negative real return on a substantial part of net assets. In other words, through the short to medium term the short-term assets contained in M3 are more attractive than longer-term investments, leading to a temporary increase in money stock M3 in Germany and France. Furthermore, we would also want to note that there is a significant divergence in the responses of the money aggregate in the core and periphery of the EA. French contribution to M3 remains within the German confidence interval through the entire horizon, Italy at the same time converges back within limits after approximately 25 months. In regard to the statistical significance of the results, also presented in Appendix D, it is suggested that the contractionary impact of the shock is statistically significant in the case of Italian and Spanish responses throughout the entire horizon. At the same time, for France the response remains statistically insignificant at first, then after approximately two years it becomes statistically significant, while the response of the contribution to M3 for Germany remains statistically insignificant for the entire horizon.

Deposit Liabilities. By comparing the dynamics of money aggregates M1 and M3 with dynamics of deposit liabilities, we observe the findings to be fairly consistent. Let us start by considering the positive spread opening between short-term rates and longer-term bond rates and the implication that short-term monetary assets (especially time-deposits) tend to earn a higher return than longer-term non-monetary assets (e.g., government bonds) in the aftermath of a monetary tightening.[69] Eventually, this finding would suggest that time deposits increase in response to a monetary tightening, partially backing our estimation results for an increase in deposit liabilities for MFIs. Of course, further research would be

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[68]Tying back to our discussion about monetary aggregate M1, sight deposits remain one of its main components, explaining why the contractionary monetary policy shock has a much smaller effect in the case of Germany. See Bundesbank (2013).

[69] Giannone, Lenza and Reichlin (2012, p.11).

necessary to determine, if the perceived safety of the core EA economies also plays an important role, in terms of all our measures and the mentioned implication for short-term monetary assets. The latter is especially relevant considering that deposit liabilities of MFIs increase for the core of the EA, remaining on a higher level as in the case of France and reversing back towards the zero line in Germany, while in the periphery, they either decrease and then they flatten as in the case of Spain, or experience an immediate and persistent decrease as in the case of Italy. The Italian impulse response is also the only that remains statistically significant for the entire horizon, while the responses for Germany, Spain and France remain insignificant. Moreover, when analyzing heterogeneity, we also see that the panel approach of our estimation results still suggests a heterogeneous behavior among the observed series.

Unlike the deposit liabilities for MFIs, NFCs have notably more negative responses. We mentioned earlier that different factors can potentially affect MFIs, however, in the case of NFC different dynamics apply. Firms are expected to meet their financial obligations relying at least in part on liquid assets following a monetary tightening. This should be especially the case in our estimation results since a significant part of our data covers the period following the financial crisis. In fact, the decrease of firms' liabilities should be mirrored by a reduction of their deposit holdings. For the EA, Pál and Ferrando (2010) have interpreted the sensitivity of firms' demand for liquid assets to cash flow as a sign of difficulties in accessing external finances. Our first observation is that deposit liabilities for NFCs have fluctuated more than those of households and non-MFIs, with partial homogeneity among countries. As we can see from Figure 2 when a monetary policy shock occurs, NFCs in Germany, Italy, and Spain immediately display negative responses, whilst the responses for France through the entire period remains positive. When it comes to France, our estimations are "puzzling" since all other countries, including Germany experience a decrease. Thus, further investigation is needed in order to address any possible issues. Additionally, similarly to deposit liabilities for MFIs Italy's and Spain's impulse responses are the only two statistically significant (albeit Italy only from period 20 onwards and Spain only from period 10 onwards).

We would also want to highlight that the reactions to a contractionary monetary policy shock, by deposit liabilities for non-MFIs are among the most homogeneous series. If we look at the responses we immediately note that except for the initial rise in France and Germany, the medium- and long-term responses are all negative and quantitatively they do not differ across countries. Regarding the statistical significance of the results for deposit liabilities of non-MFIs, we find that all the responses estimated by our FAVAR approach are statistically insignificant.

When comparing market dynamics of deposit liabilities for households to other deposit liabilities, we observe the findings to be quite singular. First, we estimate that deposit liabilities drop in Italy and France for four years following the monetary tightening. Second, we observe that in Germany deposit liabilities initially rise for one and a half years, then they stabilize. Finally, when it comes to Spain, our estimations suggest an initial rise for a period of roughly one year, then we see a reversal back to the zero line. Among all the observed measures, we consider deposit liabilities for households the most affected by the "cultural and economic diversity, which remain specific features of the EA".[70] Therefore, it does not come as a surprise that all series qualitatively respond considerably heterogeneously. It should be noted that, while in previous cases when responses were found to be heterogeneous, the distinction could be partially attributed to the difference between the core and periphery of the EA. Having said that, this case appears to be different, since no connection to other series can be made. In terms of statistical significance, all impulse responses appear to be statistically insignificant (ex-Germany for the first 20 periods).

Debt Securities Held. Having explained the impact of common monetary policy shocks on the contribution to monetary aggregates and deposit liabilities, let us look at debt securities held by MFIs and non-MFIs. Immediately, substantial responses in combination with surprising homogeneity among countries (ex-France for non-MFIs) can be noted. Overall, for most of our results in Italy and Spain, and to some

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[70] See Moutot et al. (2008, p.31).

extent also in Germany and France, we see large impulse responses for non-MFIs, with statistical significance for the latter (ex-France). A consideration is that governments, in particular, the ones in the periphery of EA needed their non-MFI (and MFIs) to finance growing public debt, after the withdrawal of foreign investors. This would possibly explain the magnitudes of the responses in the EA. At the same time, the responses tend to be less abrupt for MFIs, with France and Spain reacting most, while Germany and Italy follow. In general, we also see statistical insignificance for the responses of our MFIs series.

Long-Term Government Bond Yields. When a surprise hike in the ECB's rate hits the economies, their long-term interest rate yields reactions are surprisingly heterogeneous. Given the interconnectedness of financial markets in the EA, the expectations were for the latter to be more homogeneous than they appear. If we look back at Figure 2 the long-term interest rates first rise significantly for all four countries, then they show a falling pattern while never reaching the zero line. The impulse responses of French and German government bond yields are estimated, statistically significantly, by our FAVAR for approximately the first two years following the monetary shocks. Concurrently, in Italy and Spain, the impulse response is estimated to be statistically significant, almost throughout the entire period. According to Blaes (2009), the initial increase in the long-term interest rate can be explained by the expectation hypothesis of the term structure, which indicates that the long-term interest rate reflects an average of expected future short-term interest rates. It is also argued that the subsequent decline can presumably be attributed to the dampening effect that the monetary tightening has on the economy.

Financial Stocks. In contrast to interest rates, financial stocks respond extremely homogeneously to an exogenous interest rate shocks. Our results suggest that the impact of the shock on the financial industry is negative and persistent in all countries. One significant finding worth highlighting is that Italian and Spanish financial indices decrease less than in Germany and France. Also, after the initial decline, we can see a smoothing of the line in the long run, albeit at a slow pace. We believe that higher interest rates lead to a reduction in profit expectations since they increase financing costs and as a result affect loan demand. As stock prices

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represent the present value of all future profit expectations, they react to a positive interest rate shock by falling, too. In terms of statistical significance, the impulse responses are statistically significant for Spain, for roughly half of our 48-month horizon. Moreover, in France and Germany, the reactions remain significant for approximately three years, following a monetary policy shock. Finally, the response in Italy appears to be statistically insignificant.

Loans. With the analysis of loans, we now return to the asset side of the MFIs balance sheet. Our findings unsurprisingly show that the financial sector in aggregate responds negatively to monetary tightening, as the interest rate tightening is associated with a significant fall in total loans. We clearly see that the latter causes a negative response of loans to MFIs in all four EA economies. The reactions are most apparent for Italy and Germany, while at the same time, the response remains weaker in Spain and close to the zero line in France. Regarding the statistical significance of our findings, only the Italian and German responses are statistically significant for the entire period. Concurrently, in France and Spain, the responses remain insignificant for the entire horizon. By examining differences between countries, we discover that the response of MFIs lending is considerably homogenous since both Italian and Spanish impulse response functions lie within German confidence intervals for the entire observation span.

Furthermore, we observe significant heterogeneity in the reactions of lending to non-MFIs. Our empirical findings show that loans to non-MFIs in Germany initially respond positively to contractionary monetary policy innovation, but return to the zero line after approximately 30 months. For Spain and Italy, the reaction is negative throughout the entire period. Finally, the reaction of France is positive for the first few months, whereas the rest of the impulse response function lies in the negative region and decreases through time. In terms of the statistical significance of the responses, it is implied by our results that the tightening effect appears to be statistically significant only in France for roughly the first two years. Within approximately the first 15 months, both France and Italy fall inside German confidence bands, while afterward, only Italy remains within the area. The importance of non-MFIs and their activities vary across observed countries,

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reflecting inequalities in legal and regulatory frameworks.[71] These differences could possibly explain the heterogeneous response to a monetary policy shock.

In addition to significant heterogeneity in the reaction of lending to non-MFIs across our economies, we notice some discrepancy in the reaction to monetary tightening between MFI and non-MFI. As emphasized in the ECB analysis, these distinction between MFIs and non-MFIs in reaction to contractionary monetary policy innovation are due to the "differences in business models associated with both legal and regulatory requirements."[72,73]

Loans to NFCs respond negatively in Spain while the response in Italy is slightly positive at first, with a reversal coming only with a substantial delay. Also, in Germany and France, we observe a temporary increase in loans to NFCs. We consider the results "puzzling" since it would be expected for loans to NFC to decrease immediately after the monetary tightening. Nonetheless, similar results appear for the US when analyzed by Christiano, Eichenbaum, and Evans (1994), Gertler and Gilchrist (1993) and Den Haan et al. (2007). Moreover, Giannone et al. (2012) examined a positive and persistent reaction of loans to NFCs after a monetary tightening in the EA, emphasizing that the reaction results primarily from short-term loans to NFCs. Christiano et al. (1994) offered a possible explanation for the, at first sight, unreasonable movement when obtaining similar findings for the US. According to these authors, firms cannot modify their long-term scheduled expenses fast enough. For the statistical significance of our findings, we see that the results are statically insignificant for the impulse responses of all countries, except those of Germany and Spain, which exhibit statistical significance for approximately the first 10 months. When we look at the heterogeneity of the

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[71] See Bakk-Simon et al. (2011) and Jeffers and Plihon (2011).

[72] Zentralbank (2016).

[73] While banks have typically highly regulated capital and liquidity requirements, non-MFIs are generally not affected by public barriers and do not have access to central bank liquidity. This less regulated and consequently more flexible operating environment enables non-MFIs to make monetary transmission faster (Zentralbank, 2016).

impulses we see that both France's and Italy's impulse response functions lie within German confidence bands, signaling at least partial homogeneity in our impulse responses.

By observing the reactions of loans to households we note that both loans to households and its subcategory, i.e. loans for house purchase, react negatively to a monetary policy shock, with very similar magnitudes. For both groups, German and Italian responses are the most negative, while the responses of France and Spain are less abrupt. The responses for loans to households are statistically significant over the entire horizon for almost all countries except for Spain, where the impulses are significant for approximately a year. The analysis of statistical significance of the impulse responses for loans for house purchase implies, that only Italy and Germany are statistically significant for the entire observation span, while Spain and France are "only" significant for the first 30 and 10 months, respectively. In both groups of loans, only the German impulse response function remains within the confidence bands, implying that there are significant asymmetries in lending to households across countries. We argue that monetary tightening inflates refinancing expenditures and thus makes borrowing for households more expensive. Den Haan et al. (2007), found similar results for the US. They showed that the supply of consumer and real estate loans to households decreases during a monetary contraction. A potential explanation these authors provide is that "after a monetary tightening, after interest rates are high and economic activity low, banks prefer to invest in short-term assets, such as NFCs loans. The latter earn a high return (because short-term interest rates are high) and are relatively safer in comparison to investments in long-term and risky assets, such as real estate loans."[74]

Total Assets/Liabilities.   Lastly, when turning to the ratio of total asset/liability, we see that the responses for all the economies are negative and statistically insignificant (ex-Spain for the first 12 months). Nonetheless, the differences are relatively small across countries. We argue that the observed series, are among the

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[74] See Den Haan (2007).

most homogenous, given that impulse responses for all countries fall within German confidence bands.

In their work Boivin et al. (2008) partially address our findings of monetary aggregates. According to the authors monetary aggregates are the most heterogeneous macroeconomic variables, "a potential reflection of the pervasive differences in the national habits and the availability of savings instruments across countries of the EA" (p.96). Tying back to our discussion above and despite already providing our explanations for the heterogeneity in responses Hallett and Piscitelli (2002) list several factors we consider could likewise explain asymmetries in European monetary aggregates. To name a few, "although the overall stock of money is controlled by the ECB's interest rate, the distribution of the demand for money will vary in each country according to local conditions" (p.82). Also, "variations in the demand for money across countries (therefore) will cause differences in activity levels, differences in the supply of, and demand for credit" (p.93), which is well supported by our heterogeneous credit responses. Further, we even find confirmation in more recent literature, such as the one by Mandler et al. (2016).[75] The following determine that there is a significant disparity in the responses for loans between the Germany and the periphery of the EA. However, we could not find confirmation in the literature for a great part of our observed series. Primarily, we attribute the following to the novelty of our approach in terms of our FAVAR model, data and the analyzed time period.

Given our empirical findings and to conclude this chapter, it is crucial for us to highlight another general point made by Hallett and Piscitelli (2002). The authors state that when discussing the heterogeneity across European countries, it is possible to blame the European Monetary Union primarily for two aspects. First, the EA faces the problem of "incomplete convergence" resulting in a single policy that is inappropriate and costly due to different initial conditions. Second, there are

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[75] For studies related to heterogeneity see, i.e. Bagzibagli (2013) for confirmation of our results for loans, monetary aggregates and government bond yields. For debt securities held see, i.e. Ampudia, Pavlickova, Slacalek, and Vogel (2016).s

some "costs caused by differences in monetary responses once a shock or policy change hits the system (asymmetric transmissions)." Asymmetric transmissions appear to generate different starting points for the next period, making "unequal starting points" the main part of the "problem" when the initial conditions of the countries are equalized in the model.

5.2   Time Variation

It is so far assumed in the empirical analysis of the previous chapter that the parameters of the FAVAR models are constant over the entire sample period. In this section, however, we use a simple technique of rolling windows to analyze the potential changes in the previous findings over time and especially due to the financial and sovereign debt crisis. In addition, to the contribution of the panel approaches above, the question of time variation in cross-country heterogeneity is also of importance.

We believe that this simple technique "allows us to study the nature of the time variations while keeping computational costs manageable."[76] The rolling windows approach estimates the same model over fixed samples to assess the stability over time. As explained by Zivot and Wang (2006), "if the parameters of the model are truly constant over the entire sample, then one should expect the estimates over the rolling windows not to be too different. Also, if the parameters change at some point during the sample, then the rolling estimates should capture this instability" (p.313). Same as before we estimate our FAVAR model with a two-step estimation method, yet now for different samples rolled by 12-months. The estimation results are then compared by plotting together the impulse response functions of the main 16 variables calculated in each sample. To ensure comparability, the rolling window approach is displayed as before for all four countries and only with confidence intervals for Germany.

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[76] Canova et. al. (2012, p. 48).

5.2.1 Initial Rolling Window

Needless to say, a growing turmoil affected the financial markets in late 2007, turning into a full-fledged crisis following the collapse of Lehman Brothers in September 2008.[77] There is no doubt that the EA economies are still struggling with the aftermath of the financial and the European sovereign debt crises even when this thesis is being written in 2016-2017. That being said, what we do not know is how asymmetries change through time and if they are widening or not. Instead of setting September 2008 as the end of the initial window, we determine the initial window based upon Mario Draghi's "whatever it takes" speech from July 2012. In such way, our first data set will encompass the pre-crisis period and will end it will end by the moment that arguably "saved" the single currency. Hence, we set the initial window from 2004:9-2012:7, inclusive, we then proceed by rolling our estimations 12-months at a time.[78] Our results are presented in Appendix E.

5.2.2 Two-Step Rolling Estimation

Let us start with the rolling estimates of the impact of a contractionary monetary policy shock on our variables for the 2004:9-2012:7 period. It can be observed from Figure 7 below, that the impact of the shock is relatively homogeneous across member states. To illustrate, when our estimations include the first period, a more homogeneous impact of the shock can be observed, in comparison to our panel approach above, for the contribution to "narrow money" M1, M3, lending for house purchase, government bond yields, loans to households and deposit liabilities of MFIs. At the same time, we point out that the same estimation is more heterogeneous for loans to non-MFIs, loans to NFCs and deposit liabilities for non-MFIs. Quantitatively it is clear that the first rolling estimation is more homogeneous in comparison to our estimations encompassing the entire period from 2004:9-

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[77] Before the findings of the chapter we want to highlight that when we discuss our empirical results in the following parts of the section, we refer all the years following September 2008 until the end of our whole sample, December 2016, as the crisis period for the EA.

[78] The first observation is lost due to data transformation as explained in Section 4.1.

2016:12. Such results do not come as a surprise, as we expected more homogeneity since half of our data set for the first rolling window consists of the pre-crisis period. The responses could then be potentially attributed to the relative weight that the latter represents for our first window.

Looking further at our results in Figures 8 and 9, when we include observations following the 2004:9-2012:7 period, we initially see responses that are not significantly asymmetric across countries. Surprisingly enough for the second rolling window encompassing 2005:9-2013:7, the responses appear even more homogeneous and we see the magnitudes of the responses slightly decreasing in comparison to the first rolling window. Moving to Figure 9 representing the 2006:9-2014:7 period, we at the same time see that there are apparent differences in comparison to the first rolling window, but not as many as in the second. Parallel to the first we see from our result government bond yields, loans and most of our deposit liabilities turn out to be less abrupt (ex-loans to households and lending for house purchase), while it appears that the responses are more homogeneous. For the second, the differences are minimal both in terms of homogeneity and magnitude. In general, we would argue that the monetary policy shock hitting the economy within 2004:9-2014:7 period, has different contractionary impacts on most of our measures in terms of magnitude, but the changes appear to be small in terms of homogeneity. Moreover, we see that the buildup develops through time and at least for the first three rolling windows, it does not appear to be predetermined by any event in particular.

However, our rolling estimations clearly suggest that this homogeneity is not robust to time period changes. To illustrate, we observe qualitatively different responses between our first three rolling window and our last two. Regarding the fourth and fifth rolling window encompassing the 2007:9-2015:7 and 2007:9-2016:7 periods, respectively, we observe the full development of the buildup. Whereas the contemporaneous impact of the shock is mixed across windows, it is clear from the results, that the response for the last two windows are more sporadic than previously observed, especially for the 2008:9-2016:7 period. Also, for both windows, we find the results more heterogeneous for almost all the observed series. Most notably for

loans to households, loans for house purchase, monetary aggregates and deposit liabilities for households. We also argue that it becomes visible that the crisis still has a negative effect, in terms of cross-country heterogeneity when it comes to the transmission of the monetary shocks, besides causing more abrupt response through time.

For our concluding remarks, we would like to highlight some additional points. Firstly, it is important to note that through different periods core countries and the periphery are affected differently. As we can see from Figures 7 to 11, inclusive, the effects of the shock in Spain and Italy are for a major part worse than in France and Germany. Most notably for loans, government bond yields and deposit liabilities. We believe that these findings are of importance and in line with our findings from the previous chapter, namely that there is a significant difference between the core of the EA and its periphery. Secondly, through time different "puzzling" response apply, while the greatest concentration of such responses can be found in our last rolling window. To illustrate, loans from household and lending for house purchase increase in the case of France for the first and France, Italy and Spain for the second. Then, a common shock during the 2006:9-2014:7 period makes loans for households increase for Spain and France. Thirdly, we can see from Figures 7 to 11, inclusive, signs of variation in measures such as financial indices have almost identical contractionary impact through time (ex- the last rolling window). Finally, we believe that these findings are relevant, as they show us that the asymmetries discussed in the previous chapter, change over time.

6 Conclusion

In short then, this paper has investigated the transmission of monetary policy in the EA while focusing on the questions of cross-country heterogeneity and time variation. Similarly, to the work of B. S. Bernanke et al. (2005) a FAVAR approach is adopted, however, in our work we augment the proposed methodology with a rolling window technique. By using our novel data set for the four largest EA economies, i.e. Germany, France, Italy and Spain, we have investigated the cross-country asymmetries and time variation in the transmission of common monetary policy shocks for the period spanning from 2004:9-2016:12. Especially, we tested for possible heterogeneous effects in response to monetary tightening for the credit institutions in the four largest EA economies.

In our panel approach, we find that the contractionary impact of the monetary tightening is heterogeneous for a majority of our measures, i.e. long-term government bond yields, money supply, deposit liabilities and loans, while for most, the responses appear to be negative. The strongest impact of the shock is estimated to be for debt securities held by non-MFIs, while overall throughout the analysis we observe a persistent difference in terms of heterogeneity between the core and the periphery of the EA. Consistent with Boivin et al. (2008), who claim that monetary aggregates show more heterogeneous responses than most other macroeconomic variables, we also see our M1 and M3 measures to be among the most heterogeneous. Further, our FAVAR approach contributes to the literature by qualitatively estimating homogeneous declines in the financial indices. Our main results, as to the response of the latter can be summarized as follows: higher interest rates lead to a reduction in profit expectations since they increase financing costs and as a result affect loan demand. As stock prices represent the present value of all future profit expectations, they react to a contractionary shock by falling, too. Surprisingly, Spanish and Italian financial indices are the least affected by the monetary tightening, while overall the measure appears to be the most homogeneous from our observed variables. Finally, based on the results presented

our measures of deposit liabilities diverge considerably from country to country, with only non-MFIs and partially NFCs responding homogeneously.

Our common finding with Area, Pál and Ferrando (2010) is that firms are expected to meet their financial obligations relying at least in part on liquid assets following a monetary tightening. This is interpreted by the authors as a sign of difficulties in accessing external finances, fairly supported by the decline of our deposit liabilities for NFCs. Also, for government bond yields our results appear to be in line with Blaes (2009). Comparably, we see an initial increase in the long-term interest rate, potentially explained by the expectation hypothesis of the term structure. Additionally, we find that the model is affected only by a few "puzzles", which can be found in part of the literature and, despite the parsimonious specification, can account for the main stylized facts on the impact of monetary policy on the key macroeconomic aggregates, most notably loans to NFC.

Although the effects of the policy shocks on our whole sample approach mostly appear to be heterogeneous, we note that over time the transmission mechanism displays important differences. In the previous section, we have highlighted that according to our rolling estimations, the impact of the shock on our measures is relatively homogeneous across economies for the period spanning from 2004:9-2014:7. To illustrate, when our estimations include the first period from 2004:9-2012:7, a more homogeneous impact of the shock can be observed, in comparison to our panel approach above, for the contribution to "narrow money" M1, M3, lending for house purchase, government bond yields, loans to households and deposit liabilities of MFIs. Looking further and surprisingly enough in the second rolling window encompassing 2005:9-2013:7, the responses appear even more homogeneous and we see the magnitudes of the responses slightly decreasing in comparison to the first rolling window. At the same time, for the third rolling window we see that there are apparent differences in comparison to the first rolling window, but not as many as in the second. In general, we argue that the monetary policy shock hitting the economies within 2004:9-2014:7 period, has different contractionary impacts on most of our measures in terms of magnitude, but the changes appear to be small in terms of homogeneity. However, if we observe the

last two rolling windows 2007:9-2015:7 and 2008:9-2016:7, they clearly suggest a more heterogeneous impact of the shock. Most notably for loans to households, loans for house purchase, monetary aggregates and deposit liabilities for households. We also argue that it becomes visible that the crisis still has a negative effect, in terms of cross-country heterogeneity when it comes to the transmission of the monetary shocks, besides causing more abrupt response through time. Additional points are that through different periods core countries and the periphery are affected differently. The effects of the shock in Spain and Italy are for a major part worse than in France and Germany. Most notably for loans, government bond yields and deposit liabilities. Also, through time different "puzzling" response apply.

The main contribution of this thesis is to show with novel and most recent data set and various empirical approaches, that the responses to a monetary policy shock for the monetary aggregates, MFIs balance sheet items, financial indices, and government bond yields are heterogeneous across the four largest EA economies. We also provide the literature with empirical evidence that the responses are not only heterogeneous across the economies, but they change over time too. These findings are crucial in order to investigate whether or not "the EA monetary transmission process is uneven across countries, in a way that could complicate the conduct of the single monetary policy."[79]

Concluding, we thus believe that the main findings of the thesis contribute to the literature by providing empirical observations on an important aspect of the monetary transmission mechanism in the EA. Also, we believe our essay contributes significantly to the literature in the sense that it both supports the general conclusion of some studies cited in the text and provides empirical findings across changes in the methodology, such as time variation.

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[79] Angeloni and Ehrmann (2003, p.6).

7 References

Adrian, T., & Shin, H. S. (2009). Money, liquidity, and monetary policy.

Altavilla, C., Canova, F., & Ciccarelli, M. (2016). Mending the broken link: heterogeneous bank lending and monetary policy pass-through.

Altissimo, F., Benigno, P., & Palenzuela, D. R. (2011). Inflation differentials in a currency area: facts, explanations and policy. *Open Economies Review, 22*(2), 189-233.

Ampudia, M., Pavlickova, A., Slacalek, J., & Vogel, E. (2016). Household heterogeneity in the euro area since the onset of the Great Recession. *Journal of Policy Modeling, 38*(1), 181-197.

Andreou, E., Ghysels, E., & Kourtellos, A. (2013). Should macroeconomic forecasters use daily financial data and how? *Journal of Business & Economic Statistics, 31*(2), 240-251.

Angeloni, I., Kashyap, A. K., & Mojon, B. (2003). *Monetary policy transmission in the euro area: a study by the eurosystem monetary transmission network*: Cambridge University Press.

Ashcraft, A. B. (2006). New evidence on the lending channel. *Journal of money, Credit, and banking, 38*(3), 751-775.

Bagzibagli, K. (2013). *Cross-country heterogeneity and time variation in the euro-area economies: investigation using VAR methods.* University of Birmingham.

Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica, 70*(1), 191-221.

Bai, J., & Ng, S. (2008). Large dimensional factor analysis. *Foundations and Trends® in Econometrics, 3*(2), 89-163.

Bakk-Simon, K., Borgioli, S., Giron, C., Hempell, H. S., Maddaloni, A., Recine, F., & Rosati, S. (2011). Shadow banking in the euro area: an overview.

Banerjee, A., Marcellino, M. G., & Masten, I. (2005). Forecasting macroeconomic variables for the new member states of the European Union.

Barigozzi, M., Conti, A. M., & Luciani, M. (2014). Do euro area countries respond asymmetrically to the common monetary policy? *Oxford bulletin of economics and statistics, 76*(5), 693-714.

Barnes, S. (2010). Resolving and avoiding unsustainable imbalances. *OECD economic surveys: euro area*.

Baumeister, C., Liu, P., & Mumtaz, H. (2010). Changes in the transmission of monetary policy: Evidence from a time-varying factor-augmented VAR.

Belviso, F., & Milani, F. (2006). Structural factor-augmented VARs (SFAVARs) and the effects of monetary policy. *Topics in Macroeconomics, 6*(3).

Bernanke, B. (2004). The great moderation. *Washington, DC*.

Bernanke, B. S., & Blinder, A. S. (1992). The federal funds rate and the channels of monetary transmission. *The American Economic Review*, 901-921.

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly journal of economics, 120*(1), 387-422.

Bernanke, B. S., & Gertler, M. (1995). *Inside the black box: the credit channel of monetary policy transmission*. Retrieved from

Bernanke, B. S., & Mihov, I. (1995). *Measuring Monetary Policy*. Retrieved from

Blaes, B. (2009). Money and monetary policy transmission in the euro area: evidence from FAVAR-and VAR approaches.

Blinder, A. S. (1999). *Central banking in theory and practice*: Mit press.

Boivin, J., & Giannoni, M. (2008). *Global forces and monetary policy effectiveness*. Retrieved from

Boivin, J., Giannoni, M. P., & Mihov, I. (2009). Sticky prices and monetary policy: Evidence from disaggregated US data. *The American Economic Review, 99*(1), 350-384.

Boivin, J., Giannoni, M. P., & Mojon, B. (2008). *How has the Euro changed the monetary transmission?* Retrieved from

Boivin, J., Giannoni, M. P., & Stevanovic, D. (2009). Monetary transmission in a small open economy: More data, fewer puzzles. *Columbia University manuscript (2013)"Dynamic effects of credit shocks in a data-rich environment," CEPR discussion paper*(9470).

Braun, P. A., & Mittnik, S. (1993). Misspecifications in vector autoregressions and their effects on impulse responses and variance decompositions. *Journal of Econometrics, 59*(3), 319-341.

Bundesbank, D. (2013). Differences in money and credit growth in the Euro Area and in individual euro-area countries. *Monthly Report, Frankfurt/Main, July*, 47-63.

Canova, F., Ciccarelli, M., & Ortega, E. (2012). Do institutional changes affect business cycles? Evidence from Europe. *Journal of Economic Dynamics and Control, 36*(10), 1520-1533.

Cecioni, M., & Neri, S. (2011). The monetary transmission mechanism in the euro area: has it changed and why?

Chari, V. V., Christiano, L. J., & Eichenbaum, M. (1998). Expectation traps and discretion. *Journal of economic theory, 81*(2), 462-492.

Christiano, L. J., & Eichenbaum, M. (1992). *Liquidity effects and the monetary transmission mechanism*. Retrieved from

Christiano, L. J., Eichenbaum, M., & Evans, C. (1994). *The effects of monetary policy shocks: some evidence from the flow of funds*. Retrieved from

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (1999). Monetary policy shocks: What have we learned and to what end? *Handbook of macroeconomics, 1*, 65-148.

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of political Economy, 113*(1), 1-45.

Ciccarelli, M., Maddaloni, A., & Peydró, J.-L. (2013). Heterogeneous transmission mechanism: monetary policy and financial fragility in the eurozone. *Economic Policy, 28*(75), 459-512.

Claus, E., Claus, I., & Krippner, L. (2014). Asset markets and monetary policy shocks at the zero lower bound.

Damjanović, M., & Masten, I. (2016). Shadow short rate and monetary policy in the Euro area. *Empirica, 43*(2), 279-298.

Debrun, Xavier. 2001. "Bargaining Over EMU Vs. EMS: Why might the ECB be the Twin Sister of the Bundesbank?" The Economic Journal, 111(473): 566-590.

Dave, C., Dressler, S. J., & Zhang, L. (2009). The bank lending channel: a FAVAR analysis. *Villanova School of Busniess Economics Working Paper, 4*, 1-32.

De Santis, R. A., & Surico, P. (2013). Bank lending and monetary transmission in the euro area. *Economic Policy, 28*(75), 423-457.

Den Haan, W. J., Sumner, S. W., & Yamashiro, G. M. (2007). Bank loan portfolios and the monetary transmission mechanism. *Journal of Monetary Economics, 54*(3), 904-924.

Donald, S. G. (1997). Inference concerning the number of factors in a multivariate nonparametric relationship. *Econometrica: Journal of the Econometric Society*, 103-131.

Ehrmann, M., & Worms, A. (2001). *Interbank lending and monetary policy transmission-evidence for Germany*. Retrieved from

Eickmeier, S., & Breitung, J. (2006). How synchronized are new EU member states with the euro area? Evidence from a structural factor model. *Journal of Comparative Economics, 34*(3), 538-563.

Eickmeier, S., & Ziegler, C. (2008). How successful are dynamic factor models at forecasting output and inflation? A meta-analytic approach. *Journal of Forecasting, 27*(3), 237-265.

Enders, W. (2004). Applied econometric time series, by walter. *Technometrics, 46*(2), 264.

Everett, M. (2016). *Drivers of global liquidity and global bank flows: A view from the euro area*. Retrieved from

Favero, C. A. (2001). *Applied macroeconometrics*: Oxford University Press on Demand.

Fielding, D. and K. Shields (2011). Regional asymmetries in the impact of monetary policy shocks on prices: Evidence from US cities. Oxford Bulletin of Economics and Statistics 73, 79–103.

Forni, M., Giannone, D., Lippi, M., & Reichlin, L. (2009). Opening the black box: Structural factor models with large cross sections. *Econometric Theory, 25*(5), 1319-1347.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). The generalized dynamic-factor model: Identification and estimation. *The Review of Economics and Statistics, 82*(4), 540-554.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2004). The generalized dynamic factor model consistency and rates. *Journal of Econometrics, 119*(2), 231-255.

Forni, M., & Reichlin, L. (1998). Let's get real: a factor analytical approach to disaggregated business cycle dynamics. *The Review of Economic Studies, 65*(3), 453-473.

Gambacorta, L., & Marques-Ibanez, D. (2011). The bank lending channel: lessons from the crisis. *Economic Policy, 26*(66), 135-182.

Georgiadis, G. (2015). Examining asymmetries in the transmission of monetary policy in the euro area: Evidence from a mixed cross-section global VAR model. *European economic review, 75*, 195-215.

Gertler, M., & Gilchrist, S. (1993). The role of credit market imperfections in the monetary transmission mechanism: arguments and evidence. *The Scandinavian Journal of Economics*, 43-64.

Giannone, D., Lenza, M., & Reichlin, L. (2008). *Business cycles in the euro area*. Retrieved from

Giannone, D., Lenza, M., & Reichlin, L. (2012). Money, credit, monetary policy and the business cycle in the euro area.

Gilchrist, S., Yankov, V., & Zakrajšek, E. (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of Monetary Economics, 56*(4), 471-493.

Hahm, J. h., Shin, H. S., & Shin, K. (2013). Noncore bank liabilities and financial vulnerability. *Journal of Money, Credit and Banking, 45*(s1), 3-36.

Hallett, A. H., & Piscitelli, L. (2002). Does One Size Fit All? A currency union with asymmetric transmissions and a stability pact. *International Review of Applied Economics, 16*(1), 71-96.

Hristov, N., Hülsewig, O., & Wollmershäuser, T. (2014). The interest rate pass-through in the Euro area during the global financial crisis. *Journal of Banking & Finance, 48*, 104-119.

61

Jeffers, E., & Plihon, D. (2011). *What is so special about European Shadow banking.* Paper presented at the First International Conference of Cost Action IS0902 Program «Systemic Risks, Financial Crises, and Credit», Université Paris.

Jimborean, R., & Mésonnier, J.-S. (2010). Banks' financial conditions and the transmission of monetary policy: a FAVAR approach.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. *The Review of Economics and Statistics, 80*(2), 218-230.

Kilian, L. (2012). Structural Vector Autoregressions.

Kim, H. J., Shin, H. S., & Yun, J. (2013). Monetary aggregates and the central bank's financial stability mandate. *International Journal of Central Banking, 9*(1), 69-108.

Krippner, L. (2013). A tractable framework for zero-lower-bound Gaussian term structure models.

Krippner, L. (2015). *Zero lower bound term structure modeling: A practitioner's guide*: Springer.

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics, 47*(3), 523-544.

Lagana, G., & Mountford, A. (2005). MEASURING MONETARY POLICY IN THE UK: A FACTOR-AUGMENTED VECTOR AUTOREGRESSION MODEL APPROACH. *The Manchester School, 73*(s1), 77-98.

Lewbel, A. (1991). The rank of demand systems: theory and nonparametric estimation. *Econometrica: Journal of the Econometric Society*, 711-730.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*: Springer Science & Business Media.

Lütkepohl, H., & Krätzig, M. (2004). *Applied time series econometrics*: Cambridge university press.

Mandler, M., Scharnagl, M., & Volz, U. B. (2016). Heterogeneity in euro-area monetary policy transmission: Results from a large multi-country BVAR model.

Mihov, I. (2001). Monetary policy implementation and transmission in the European Monetary Union. *Economic Policy, 16*(33), 370-406.

Moutot, P., Jung, A., & Mongelli, F. P. (2008). The working of the eurosystem: monetary policy preparations and decision-making-selected issues.

MSCI index calculation methodology. (October 6, 2017). Retrived from

https://www.msci.com/eqb/methodology/meth_docs/MSCI_September2017_IndexCalcMethodology.pdf

MSCI Spain financials index. (October 6, 2017). Retrieved from
https://www.msci.com/documents/10199/80fa900b-dc2c-4a40-b7eb-bf04f78ba8ee

Pál, R., & Ferrando, A. (2010). Financing constraints and firms' cash policy in the euro area. *The European Journal of Finance, 16*(2), 153-171.

Peersman, G., & Smets, F. (2001). The monetary transmission mechanism in the euro area: more evidence from VAR analysis (MTN conference paper).

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of economic theory, 13*(3), 341-360.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1-48.

Sims, C. A. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European economic review, 36*(5), 975-1000.

Sims, C. A., & Zha, T. (1998). Bayesian methods for dynamic multivariate models. *International Economic Review*, 949-968.

Smets, F., & Wouters, R. (2005). Comparing shocks and frictions in US and euro area business cycles: a Bayesian DSGE approach. *Journal of Applied Econometrics, 20*(2), 161-183.

Sousa, J. M., & Zaghini, A. (2007). Global monetary policy shocks in the G5: A SVAR approach. *Journal of International Financial Markets, Institutions and Money, 17*(5), 403-419.

Stock, J. H., & Watson, M. W. (1998). *Diffusion indexes*. Retrieved from

Stock, J. H., & Watson, M. W. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American statistical association, 97*(460), 1167-1179.

Stock, J. H., & Watson, M. W. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics, 20*(2), 147-162.

Stock, J. H., & Watson, M. W. (2005). *Implications of dynamic factor models for VAR analysis*. Retrieved from

Strongin, S. (1995). The identification of monetary policy disturbances explaining the liquidity puzzle. *Journal of Monetary Economics, 35*(3), 463-497.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics, 52*(2), 381-419.

Weber, A. A., Gerke, R., & Worms, A. (2009). Has the monetary transmission process in the euro area changed? Evidence based on VAR estimates.

Woodford, M. (2005). *Central bank communication and policy effectiveness*. Retrieved from

Wu, J. C., & Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking, 48*(2-3), 253-291.

Zivot, E., & Wang, J. (2006). Modelling financial time series with S-PLUS. *Springer*, 429-478.

Zentralbank, E. (2009). Annual report 2008., European Central Bank, 1-284. Retrived   from https://www.ecb.europa.eu/pub/pdf/annrep/ar2008en.pdf?0eac7e7bc25a89 2243f0aa008878834ascas

Zentralbank, E. (2016). The role of euro area non-monetary financial intermediation. ECB Economic Bulletin, (4), 1-19. Retrived from https://www.ecb.europa.eu/pub/pdf/other/eb201604_article01.en.pdf?f0bff a04b7b1e638cf170371d41d3cb7

Appendix A - Data Description

The data we use in our empirical model are summarized in the following two tables. The first table contains macroeconomic variables, while the second table contains monetary financial institution (MFI) balance sheet items. Details about the applied transformation (Tr.) are presented in the third column and the distinction between slow- and fast-moving variables in the fourth column. The transformation marks are 1 – no transformation; 2 – first difference, 5 – first difference of logarithm. In the fourth column, "0" denotes fast-moving variables while "1" denotes for slow-moving variables.

Table 1: Macroeconomic Data

NO.	DESCRIPTION	TR.	S/F	SOURCE
1	IP Total (2010 =100)	5	1	Eurostat
2	IP - Intermediate Goods	5	1	Eurostat
3	IP – Energy	5	1	Eurostat
4	IP – Capital Goods	5	1	Eurostat
5	IP - Durable Consumer Goods	5	1	Eurostat
6	IP – Non – Durable Consumer Goods	5	1	Eurostat
7	IP – Mining and Quarrying	5	1	Eurostat
8	IP – Manufacturing	5	1	Eurostat
9	IP – Construction	5	1	Eurostat
10	Unemployment Rate (%)	1	1	Eurostat
11	Youth Unemployment Rate	1	1	Eurostat
12	Unemployment Total (25-74 years)	1	1	Eurostat
13	Ratail Trade (2010 = 100) (WDA)	5	1	Bloomberg
14	Exports Total	5	1	Bloomberg
15	Imports Total	5	1	Bloomberg
16	HICP - All items	1	1	Eurostat
17	HICP – Energy and Unprocessed Food (2005 = 100)	5	1	Eurostat
18	HICP – Liquid Fuels and Lubricants (2005 = 100)	5	1	Eurostat

NO.	DESCRIPTION	TR.	S/F	SOURCE
19	HICP – Goods	5	1	Eurostat
20	HICP – Services	5	1	Eurostat
21	HICP – No-Energy Ind. Goods, Non – Durable	5	1	Eurostat
22	HICP – No-Energy ind. Goods, Durable	5	1	Eurostat
23	PPI – Industry	5	1	Eurostat
24	PPI – Manufacturing	5	1	Eurostat
25	PPI - Mining and Quarrying	5	1	Eurostat
26	PPI - Durable Consumer Goods	5	1	Eurostat
27	PPI - Non-Durable Consumer Goods	5	1	Eurostat
28	5Y Government Bond Yield	1	0	Bloomberg
29	10Y Government Bond Yield	1	0	Bloomberg
30	Spread 5Y – REFI*	1	0	Calculated
31	Spread 10Y - REFI*	1	0	Calculated
32	Overall Share Price Index	5	0	Bloomberg
33	MSCI Financial Index	5	0	Bloomberg
34	Share Price Index - Basic Materials	5	0	FTSE
35	Share Price Index - Industrials	5	0	FTSE
36	Share Price Index - Consumer Services	5	0	FTSE
37	Share Price Index - Telecommunication	5	0	FTSE
38	Share Price Index - Utilities	5	0	FTSE
39	Monetary Base, Currency in Circulation (Mil. Euro)	5	0	IMF
40	Capital and Reserves (Mil. Euro)	5	0	ECB
41	Money Supply M1	5	0	National Institutes and ECB
42	Money Supply M2	5	0	National Institutes and ECB
43	Money Supply M3	5	0	National Institutes and ECB

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NO.	DESCRIPTION	TR.	S/F	SOURCE
44	Economic Sentiment Indicator (Index)	5	0	DG ECFIN Directorate General for Economic and Financial Affairs
45	Construction Confidence Indicator	1	0	DG ECFIN Directorate General for Economic and Financial Affairs
46	Industrial Confidence Indicator	1	0	DG ECFIN Directorate General for Economic and Financial Affairs
47	Retail Confidence Indicator	1	0	OECD
48	Consumer Confidence Indicator	5	0	OECD
49	Services Confidence Indicator	1	0	OECD
50	Production Expectation for the Months Ahead	1	0	DG ECFIN Directorate-General for Economic and Financial Affairs
51	EC Consumer confidence price trends over the next months	1	0	Bloomberg
52	Crude oil (West Texas Int., $/BBL)	5	0	Thomson Reuters
53	CRB Spot Index (1957=100)	5	0	Thomson Reuters
54	S&P GSCI Gold Total Return	5	0	Thomson Reuters
55	Gold Bullion LBM U$/Troy Ounce	5	0	Thomson Reuters
56	S&P GSCI Enhanced Commodity PI	5	0	Thomson Reuters
57	3M Euribor (%)	1	0	Bloomberg
58	6M Euribor	1	0	Bloomberg
59	9M Euribor	1	0	Bloomberg
60	1Y Euribor	1	0	Bloomberg
61	Spread 3M – REFI*	1	0	Calculated
62	Spread 6M – REFI*	1	0	Calculated
63	Spread 1Y – REFI*	1	0	Calculated
64	Euro Stoxx 50	5	0	Bloomberg
65	IP-USA	5	1	Bloomberg
66	IP-UK	5	1	Bloomberg
67	IP-JP	5	1	Bloomberg

NO.	DESCRIPTION	TR.	S/F	SOURCE
68	CPI – USA	5	1	Thomson Reuters
69	CPI – UK	5	1	Thomson Reuters
70	CPI -JP	5	1	Thomson Reuters
71	US Federal Funds Target Rate (%)	1	0	Bloomberg
72	UK Bank of England Base Rate	1	0	Bloomberg
73	JP Overnight Call Money Rate	1	0	Bloomberg
74	10 Y Bond Yield USA	1	0	Thomson Reuters
75	10 Y Bond Yield UK	1	0	Thomson Reuters
76	10 Y Bond Yield Switzerland	1	0	Thomson Reuters
77	10 Y Bond Yield Japan	1	0	Thomson Reuters
78	Share Price Index USA (S&P 500)	5	0	Standard and Poor's
79	Share Price Index UK (FTSE 350)	5	0	FTSE
80	Share Price Index Japan (Nikkei 225)	5	0	Nikkei
81	US Dollar - Euro (Exchange rate)	5	0	Thomson Reuters
82	Pound Sterling - Euro	5	0	Thomson Reuters
83	Swiss Franc - Euro	5	0	Thomson Reuters
84	Japanese Yen - Euro	5	0	Thomson Reuters
85	REER (1999 = 100)	5	0	IMF – International Financila Statistics
86	Shadow Rate	1	0	Wu-Xia Shadow Rates

Table 2: Monetary Financial Institutions Balance Sheet Items

NO.	DESCRIPTION	TR.	S/F	SOURCE
1	Loans, Other Euro area member states, Monetary financial institutions (MFIs)	5	0	ECB Statistical Data Warehouse
2	Loans, Other Euro area member states, Non-MFIs	5	0	ECB Statistical Data Warehouse
3	Loans, Other Euro area member states, Non-Financial corporations (NFCs)	5	0	ECB Statistical Data Warehouse

NO.	DESCRIPTION	TR.	S/F	SOURCE
4	Loans, Other Euro area member states, Households	5	0	ECB Statistical Data Warehouse
5	Loans, Domestic, MFIs	5	0	ECB Statistical Data Warehouse
6	Loans, Domestic, Non-MFIs	5	0	ECB Statistical Data Warehouse
7	Loans, Domestic, General Government	5	0	ECB Statistical Data Warehouse
8	Loans, Domestic, NFCs	5	0	ECB Statistical Data Warehouse
9	Loans, Domestic, Households	5	0	ECB Statistical Data Warehouse
10	Lending for house purchase, Domestic, Households	5	0	ECB Statistical Data Warehouse
11	Debt securities held, Other Euro area member states, MFIs	5	0	ECB Statistical Data Warehouse
12	Debt securities held, Other Euro area member states, Non-MFIs	5	0	ECB Statistical Data Warehouse
13	Debt securities held, Other Euro area member states, General Government	5	0	ECB Statistical Data Warehouse
14	Debt securities held, Domestic, MFIs	5	0	ECB Statistical Data Warehouse
15	Debt securities held, Domestic, Non-MFIs	5	0	ECB Statistical Data Warehouse
16	Debt securities held, Domestic, General Government	5	0	ECB Statistical Data Warehouse
17	Equity and non-MMF investment fund shares/units, MFIs	5	0	ECB Statistical Data Warehouse
18	Equity and non-MMF investment fund shares/units, Non-MFIs excluding general government	5	0	ECB Statistical Data Warehouse
19	Deposit liabilities, Other Euro area member states, MFIs	5	0	Eurostat
20	Deposit liabilities, Other Euro area member states, Non-MFIs	5	0	ECB Statistical Data Warehouse

NO.	DESCRIPTION	TR.	S/F	SOURCE
21	Deposit liabilities, Other Euro area member states, NFCs	5	0	ECB Statistical Data Warehouse
22	Deposit liabilities, Other Euro area member states, Households	5	0	ECB Statistical Data Warehouse
23	Deposit liabilities, Domestic, MFIs	5	0	ECB Statistical Data Warehouse
24	Deposit liabilities, Domestic, Non-MFIs	5	0	ECB Statistical Data Warehouse
25	Deposit liabilities, Domestic, Non-Financial Corporations	5	0	ECB Statistical Data Warehouse
26	Deposit liabilities, Domestic, Households	5	0	ECB Statistical Data Warehouse
27	Money Market Funds shares/units, Euro area (changing composition), Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse
28	Money Market Funds shares/units, World not allocated (geographically), Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse
29	Capital and reserves, World not allocated (geographically), Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse
30	Remaining liabilities, World not allocated (geographically), Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse
31	External liabilities, Extra Euro area, Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse
32	Total Assets/Liabilities, Total, World not allocated (geographically), Unspecified counterpart sector	5	0	ECB Statistical Data Warehouse

Appendix B - Identification of Monetary Policy Shocks

We already mentioned that monetary policy shocks are considered as "unanticipated/surprise" changes in the monetary policy. In other words, we may say that they arise as errors of assessment of the economic situation by the central banks. For a better understanding of how these dynamics work, we shortly show the scheme algebraically.

Christiano et al. (1999) identified a monetary policy shock as a disturbance form in the following equation:

$$S_t = f(\Omega_t) + \sigma_s \varepsilon_t^s \tag{B.0.1}$$

Here S_t denotes for an instrument of monetary authority, for example central bank's interest rate or some monetary aggregate. While f is a linear function that captures monetary authority's response, Ω_t represents their information set. The monetary policy shock is determined by a random variable $\sigma_s \varepsilon_t^s$, where ε_t^s is normalized to have a unit variance, and σ_s denotes a standard deviation of the monetary policy shock.

The equation (B.0.1) can be thoroughly broken down. Suppose that the monetary authority determines the policy variable S_t as an exact function of current and lagged observations on a collection of variables, x_t. The $x_t(0)$ and $x_{t-1}(1)$ represent the time t observations on x_t and x_{t-1} where:

$$x_t(0) = x_t + v_t \ \ and \ \ x_{t-1}(1) = x_{t-1} + u_{t-1} \tag{B.0.2}$$

Here v_t determines the simultaneous measurement error in x_t, whereas u_t denotes the measurement error in x_t from the perspective of period $t + 1$. When x_t is perfectly observed with a one period delay, then $u_t \equiv 0$ for every t. Assume that the monetary authority determines S_t as follows:

$$S_t = \beta_0 S_{t-1} + \beta_1 x_t(0) + \beta_2 x_{t-1} \tag{B.0.3}$$

Expressed in terms of correctly measured variables, this policy rule transforms the equation (B.0.1) into:

$$S_t = \beta_0 S_{t-1} + \beta_1 x_t + \beta_2 x_{t-1} + \beta_1 v_t + \beta_2 u_{t-1} \tag{B.0.4}$$

where

$$f(\Omega_t) = \beta_0 S_{t-1} + \beta_1 x_t + \beta_2 x_{t-1} \qquad (\text{B.}\,0.5)$$

$$\sigma_s \varepsilon_t^S = \beta_1 v_t + \beta_2 u_{t-1} \qquad (\text{B.}\,0.6)$$

This example demonstrates how a disturbance in data collection process can be a source of exogenous variation in monetary policy shock (Christiano, Eichenbaum, and Evans, 1999). Moreover, the example can be used to demonstrate how interpretation of the error term can impact the validity of alternative presumptions used to identify ε_t^S. Recall the recursiveness assumption, which presumes that ε_t^S is orthogonal to elements of information set Ω_t. In order to clarify when the reclusiveness assumption holds under the measurement error interpretation, let us assume that v_t and u_t are uncorrelated with x_t at all leads and lags. If $\beta_0 = 0$, then the reclusiveness assumption holds. Furthermore, this assumption is satisfied as well when $\beta_0 \neq 0$ and $u_t \equiv 0$. Nevertheless, when $\beta_2 \neq 0, u_t \neq 0$ and u_t and v_t are correlated, the reclusiveness assumption fails. In words of Christiano et al. 1999, the last case, provides an important notice to measurement error as an interpretation of monetary policy shocks estimated by analysts who exploit the reclusiveness assumption. Since in developing identifying constraints, analysts typically abstract from the likelihood of measurement error, the three authors presume that this may also be true for analysis which do not impose reclusiveness assumption.

Appendix C - Factor Analysis

Following the steps of Bai and Ng (2002), we propose an even closer inspection of the theoretical estimation of factor models and the correct specification of the number of factors. The estimation procedure is proposed first, then a summary of Bai and Ng's approach for the estimation of the number of factors is reviewed.

Factor Model

To estimate common factors in large panels like equation $X_{it} = \lambda_i' F_t + e_{it}$, Bai and Ng (2002) use the method of asymptotic principal components. The authors claim that the number of factors that can be estimated by this non-parametric method is *min*{N, T}. The latter is musch larger than permitted by the estimation of state space models. To determine the statistical importance of these factors, Bai and Ng (2002) highlight the necessity to first establish consistency of all estimated factors, while both T and N are large, and consider an arbitrary number *k, k < min* {N, T}, to start with. We obtain estimations of λ^k and F^k , by solving the following optimization problem:

$$V(k, F^k) = \min_{\Lambda, F^k} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda_i^{k'} F_i^{k'} \right)^2 \tag{C.0.1}$$

subject to the normalization of either $\frac{\Lambda^{k'} \Lambda^k}{N} = I_k$ or $\frac{F^{k'} F^k}{T} = I_k$.

Focusing on Λ^k and using the latter normalization leads the optimization problem to be identical to maximizing $tr(F^{k'}(XX')F^k)$. The authors list two possible solutions to the minimization problem above: (i) where the estimated factor matrix, $\widetilde{F^k}$, is$\sqrt{T}$ times the eigenvectors corresponding to the *k* largest eigenvalues of the *T* x *T* matrix XX', and given $\widetilde{F^k}$ the corresponding matrix of factor loadings is $\widetilde{\Lambda^{k'}} = (\widetilde{F^{k'}} \widetilde{F^k})^{-1} \widetilde{F^{k'}} X = \widetilde{F^{k'}} X / T$ or (ii) by $(\overline{F^k}, \overline{\Lambda^k})$ where $\overline{\Lambda^k}$ is constructed as $\sqrt{N}$ times the eigenvectors corresponding to the *k* largest eigenvalues of the *N* x *N* matrix $X'X$. The normalization that $\frac{\Lambda^{k'} \Lambda^k}{N} = I_k$, employed in the second solution, implies $\overline{F^k} = \frac{X \overline{\Lambda^k}}{N}$. In this optic, adding the second solution is crucial due to the fact

that "the (former) solution is not unique, even though the sum of squared residuals $V(k)$ is unique".[80] In regard to the intensity of computation of the solutions, we could say the second set of calculations is less costly when $T > N$, while the firs is less intense when the reverse is true.

Estimation of Number of Factors

Now that we described the model and its estimation, we move to the determination of the number of static factors.

Because of the linearity of the model and the factors being observable, it is possible to estimate λ_i by applying ordinary least squares to each equation. Therefore, Bai and Ng describe the case as a classical model selection problem.

If we assume that F^k is a matrix of k factors, then we can show the sum of squared residuals (divided by NT) from time-series regressions of X_i on the k factor for all i as:

$$V(k, F^k) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (X_{it} - \lambda_i^{k'} F_i^{k'})^2 \qquad (C.0.2)$$

then our purpose is to find specific penalty functions, g(N, T), such that criteria of the form:

$$PC(K) = V\left(\widehat{\Lambda_k}, \widehat{F_k}\right) + kg(N, T) \qquad (C.0.3)$$

can consistently estimate the true common factors *r*. Additionally, Bai and Ng propose another class of criteria defined by:

$$IC(K) = ln\left(V(\widehat{\Lambda_k}, \widehat{F_k})\right) + kg(N, T) \qquad (C.0.4)$$

which also estimates *r* consistently. In this setup $V\left(\widehat{\Lambda_k}, \widehat{F_k}\right)$ represents the sum of squared residuals of a k-factor model. At the same time, $\widehat{\Lambda_k}$ and $\widehat{F_k}$ are estimates of factors and loadings from the k-factor model, while g(N,T) is the already mentioned

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[80] Bai and Ng (2002)

penalty fiction, that approaches zero and min{N,T} g(N,T) goes to infinity as (N,T) goes to infinity. Under the assumption that the factors are estimated by the method of PC, the authors propose the following formulations of g(N, T) in $PC(k)$ and $IC(k)$:

$$PC_{p1}(k) = V\left(k, \widehat{F^k}\right) + k\widehat{\sigma^2}\left(\frac{N+T}{NT}\right) ln\left(\frac{NT}{N+T}\right) \tag{C.0.5}$$

$$PC_{p2}(k) = V\left(k, \widehat{F^k}\right) + k\widehat{\sigma^2}\left(\frac{N+T}{NT}\right) ln C_{NT}^2 \tag{C.0.6}$$

$$PC_{p3}(k) = V\left(k, \widehat{F^k}\right) + k\widehat{\sigma^2}\left(\frac{ln C_{NT}^2}{C_{NT}^2}\right) \tag{C.0.7}$$

$$IC_{p1}(k) = \ln(V\left(k, \widehat{F^k}\right)) + k\left(\frac{N+T}{NT}\right) ln\left(\frac{NT}{N+T}\right) \tag{C.0.8}$$

$$IC_{p2}(k) = \ln\left(V\left(k, \widehat{F^k}\right)\right) + k\left(\frac{N+T}{NT}\right) ln C_{NT}^2 \tag{C.0.9}$$

$$IC_{p3}(k) = \ln\left(V\left(k, \widehat{F^k}\right)\right) + k\left(\frac{ln C_{NT}^2}{C_{NT}^2}\right) \tag{C.0.10}$$

According to the authors, in addition to being a superior theory, by reason of allowing weak serial and cross-section dependence, the technique has several other advantages:(i) it does not rely on sequential limits, (ii) it does not impose any restrictions between N and T, (ii) the outcome holds-under-heteroscedasticity in both cross-section dimensions and time, and (iv) simulations run by Bai and Ng show that the criteria have good finite sample properties. Finally, in regard to the information criterion used in the analysis, Bai and Ng state that the main advantage of the latter and other panel information criteria (IC_p) is that they do not depend on the choice of kmax (maximum number of factors allowed) through σ^2, where $V\left(k, \widehat{F^k}\right) = N^{-1} \sum_{i=1}^{N} \widehat{\sigma_i^2}$, and $\widehat{\sigma_i^2} = \frac{\widehat{e_i'}\widehat{e_i}}{T}$ from equation $X_{it} = \lambda_i' F_t + e_{it}$.

Appendix D - Panel Approach

In the following part, it is possible to find our results from section 5.1. In Figures 2 to 6 we present impulse responses following a monetary policy shock defined as an exogenous innovation in the ECB shadow rate of 25-basis-points and identified using B.S. Bernanke et al. (2005) identification scheme. Figure 2 corresponds to the cross-country heterogeneity – panel estimation approach, from which we determine the heterogeneity between countries. In interpreting the impulse response distributions, we base our assessment on whether the responses for Italy, Spain, and France are located within or outside the 68% German confidence bands. Moreover, subsequent to the main results in Figure 2, it is possible to find each country, i.e. Germany, Italy, Spain and France impulse response functions, with the respective 68% confidence intervals.
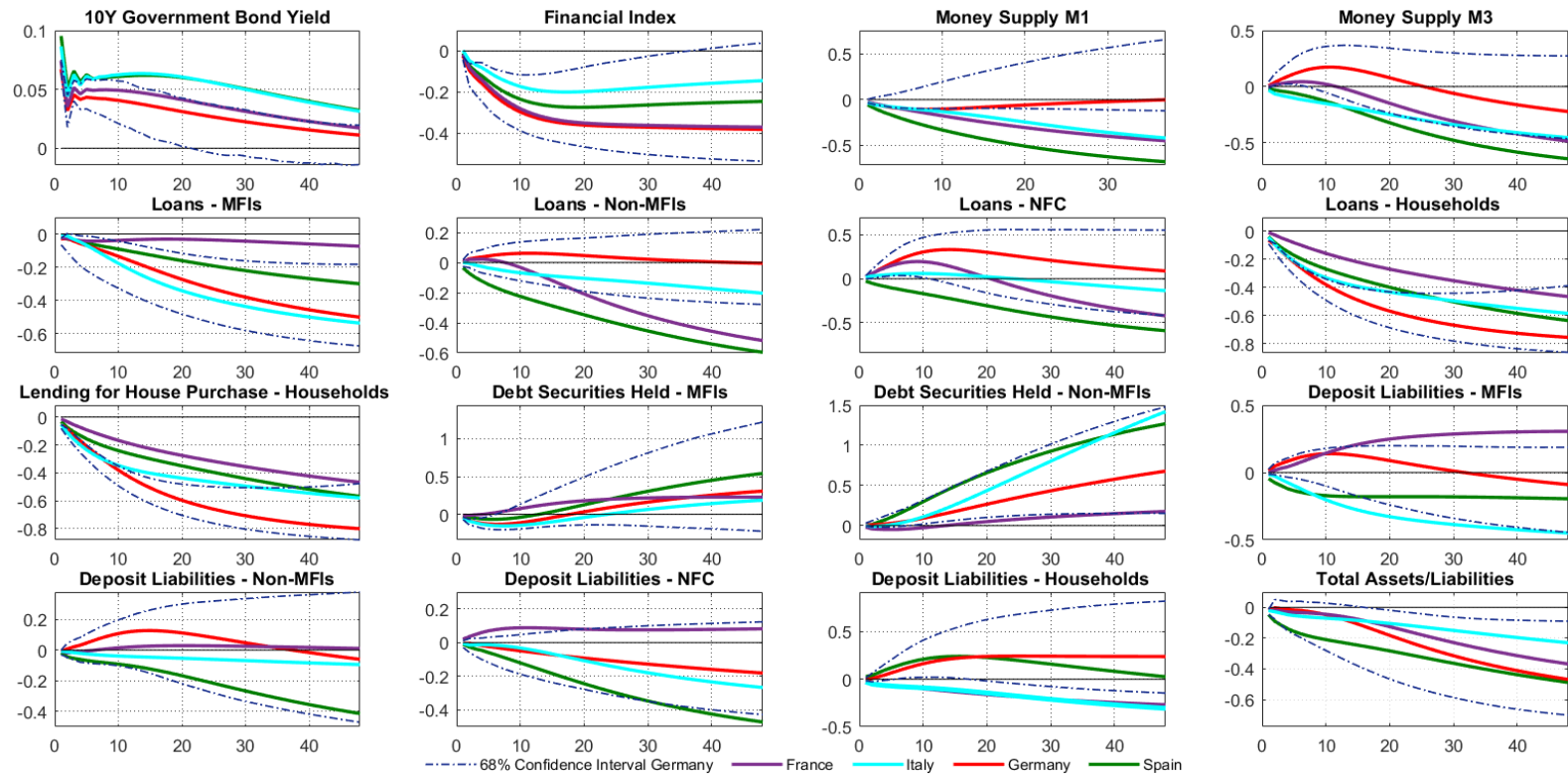
Figure 2: Cross-Country Heterogeneity - Panel Estimation
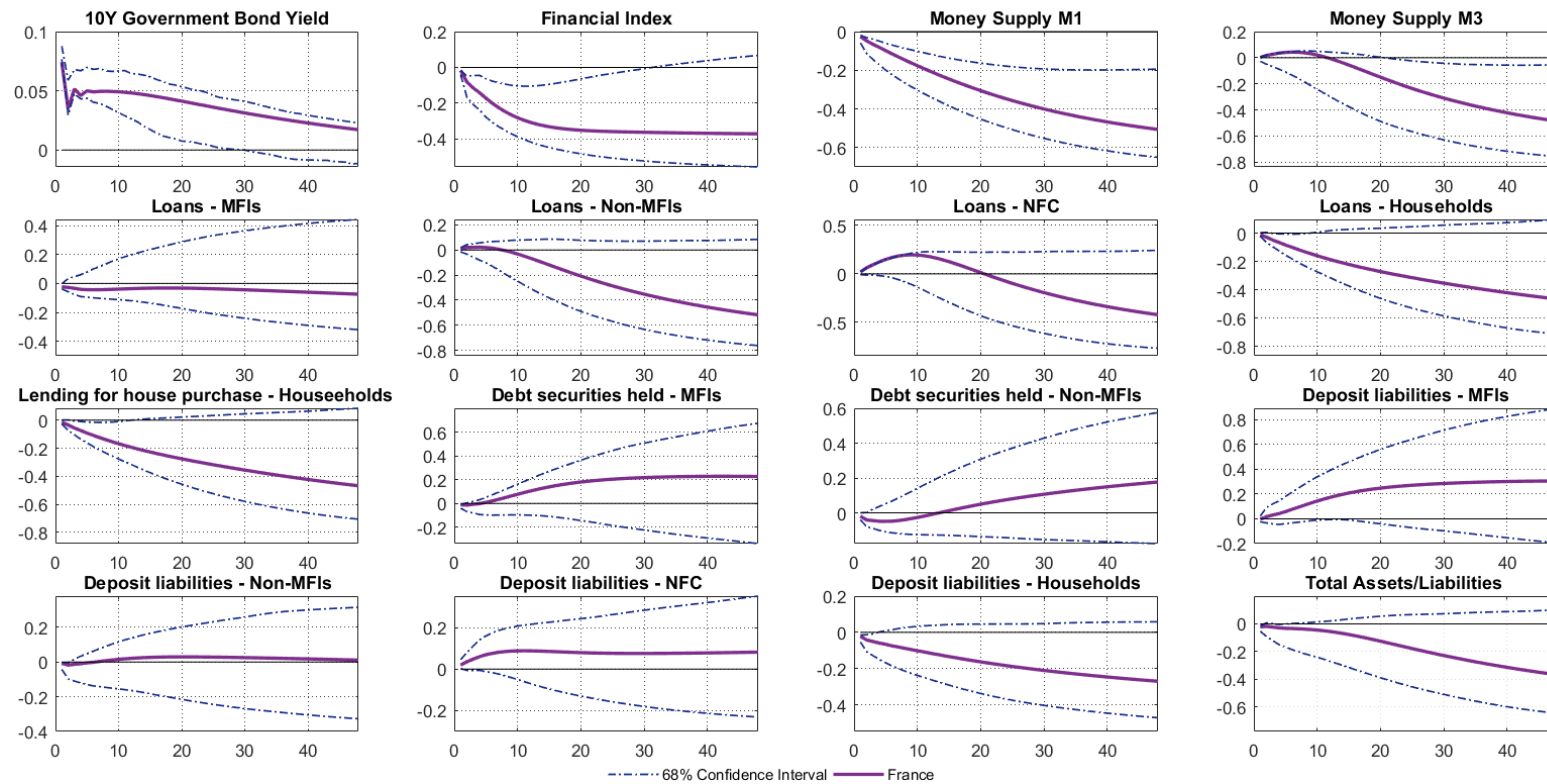
Figure 3: Confidence Intervals - France
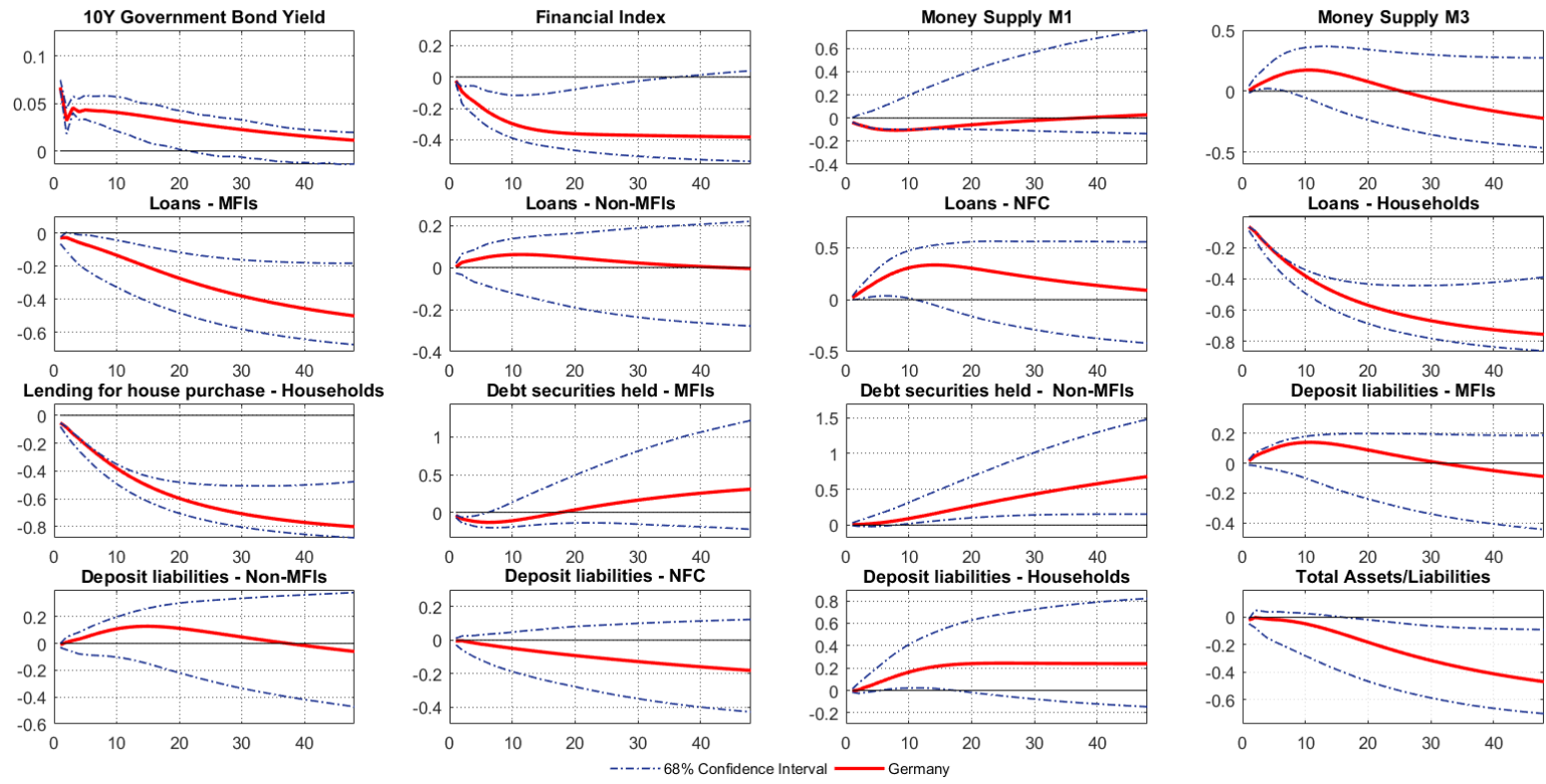
Figure 4: Confidence Intervals - Germany
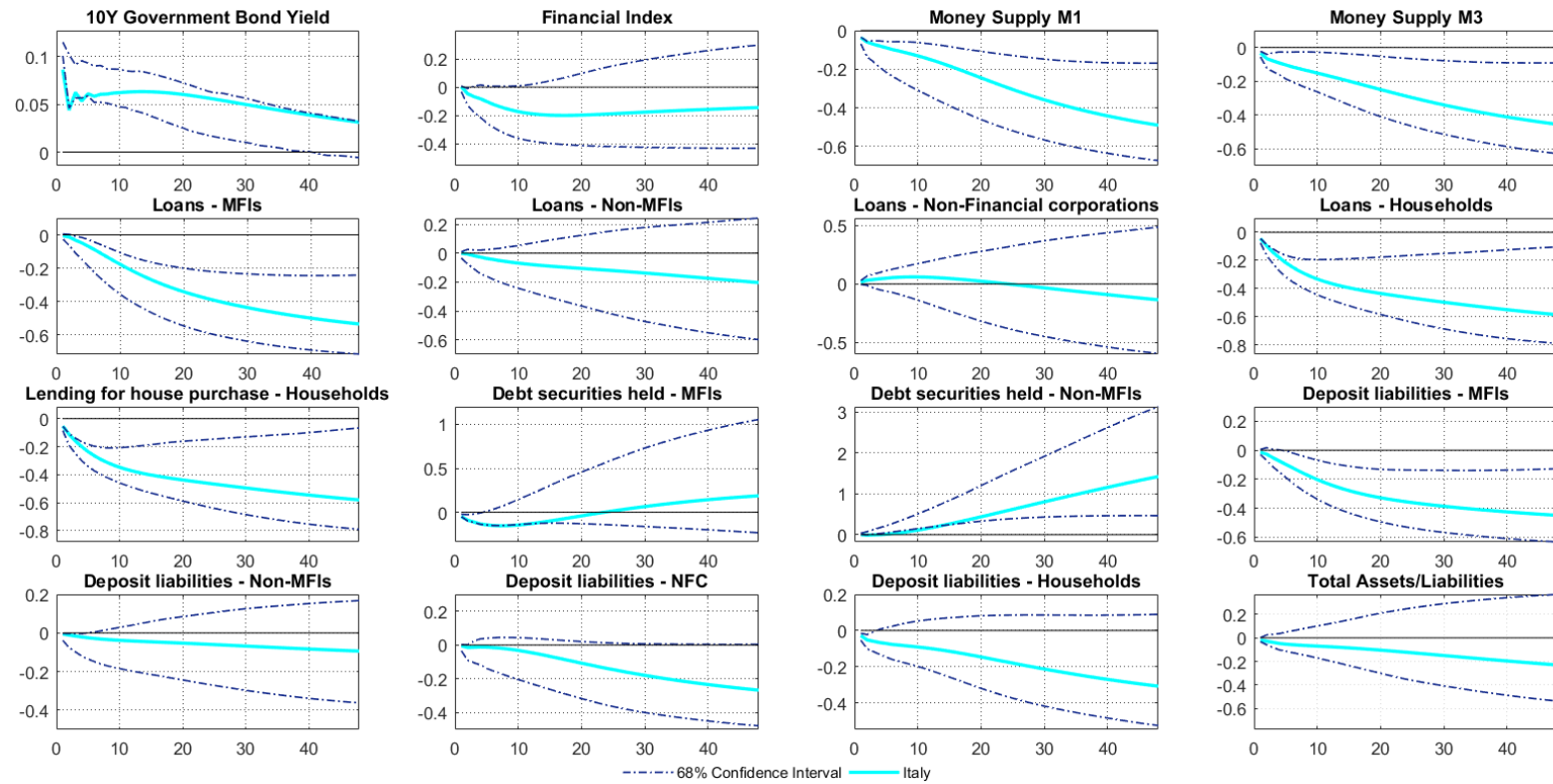
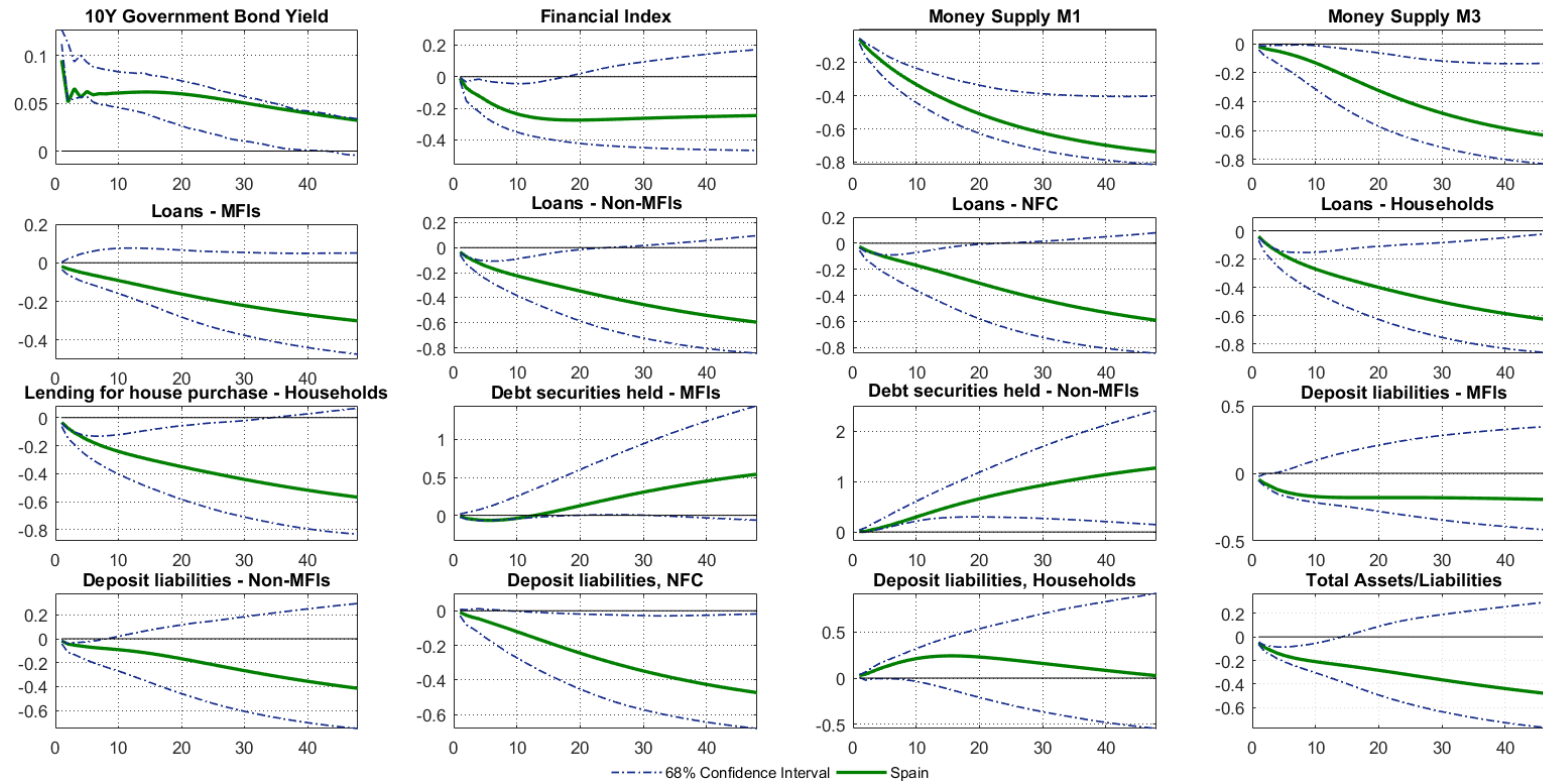*Figure 5: Confidence Intervals - Italy*

80

Figure 6: Confidence Intervals - Spain

Appendix E - Rolling Windows

In the following part, it is possible to find our results from section 5.2. The first figure corresponds to the cross-country heterogeneity – rolling windows approach, from which we determine the heterogeneity between countries over time. Our first period of observation corresponds to 2004:9-2012:7, then we proceed by rolling for 12 months at a time. Again, our estimation is based upon monetary policy shock defined as an exogenous innovation in the ECB shadow rate of 25-basis-points and identified using B.S. Bernanke et al. (2005) identification scheme. Also, when interpreting the impulse response distributions, we base our assessment on whether the responses for Italy, Spain, and France are located within or outside the 68% German confidence bands, while we keep the same scales for all plots to ensure better comparability between periods.
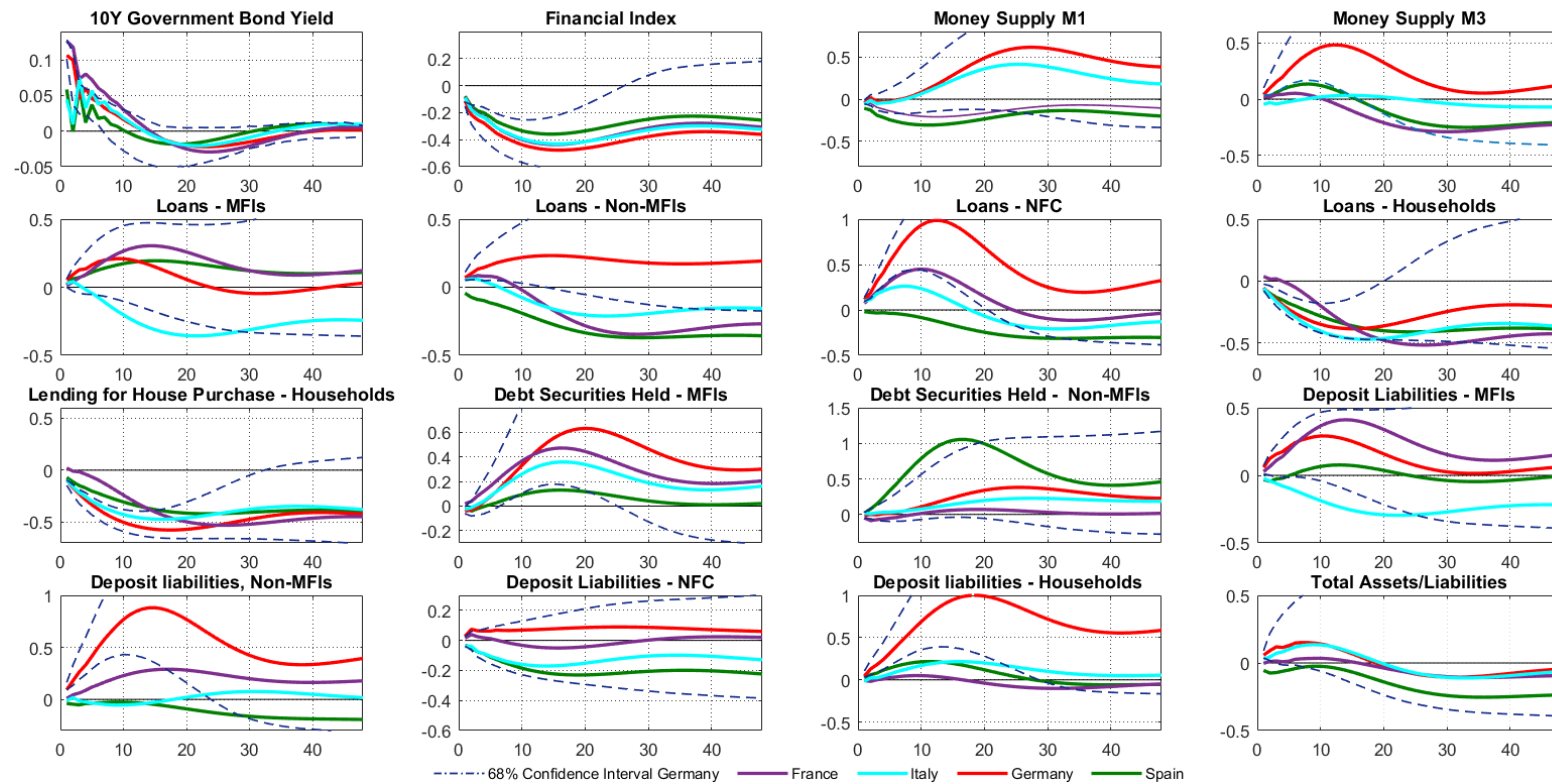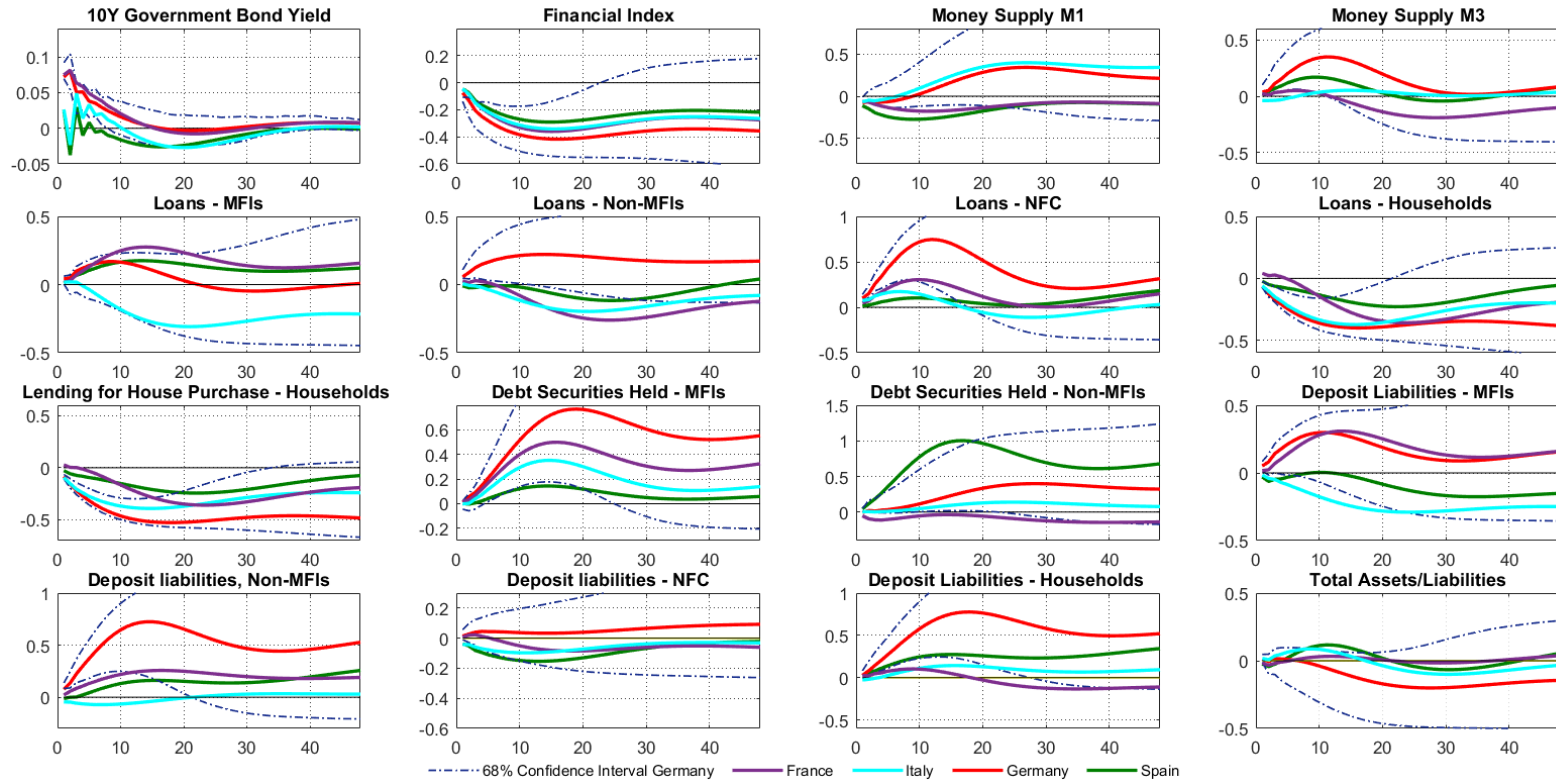
Figure 7: Rolling Windows 2004:9-2012:7 – Two Step FAVAR
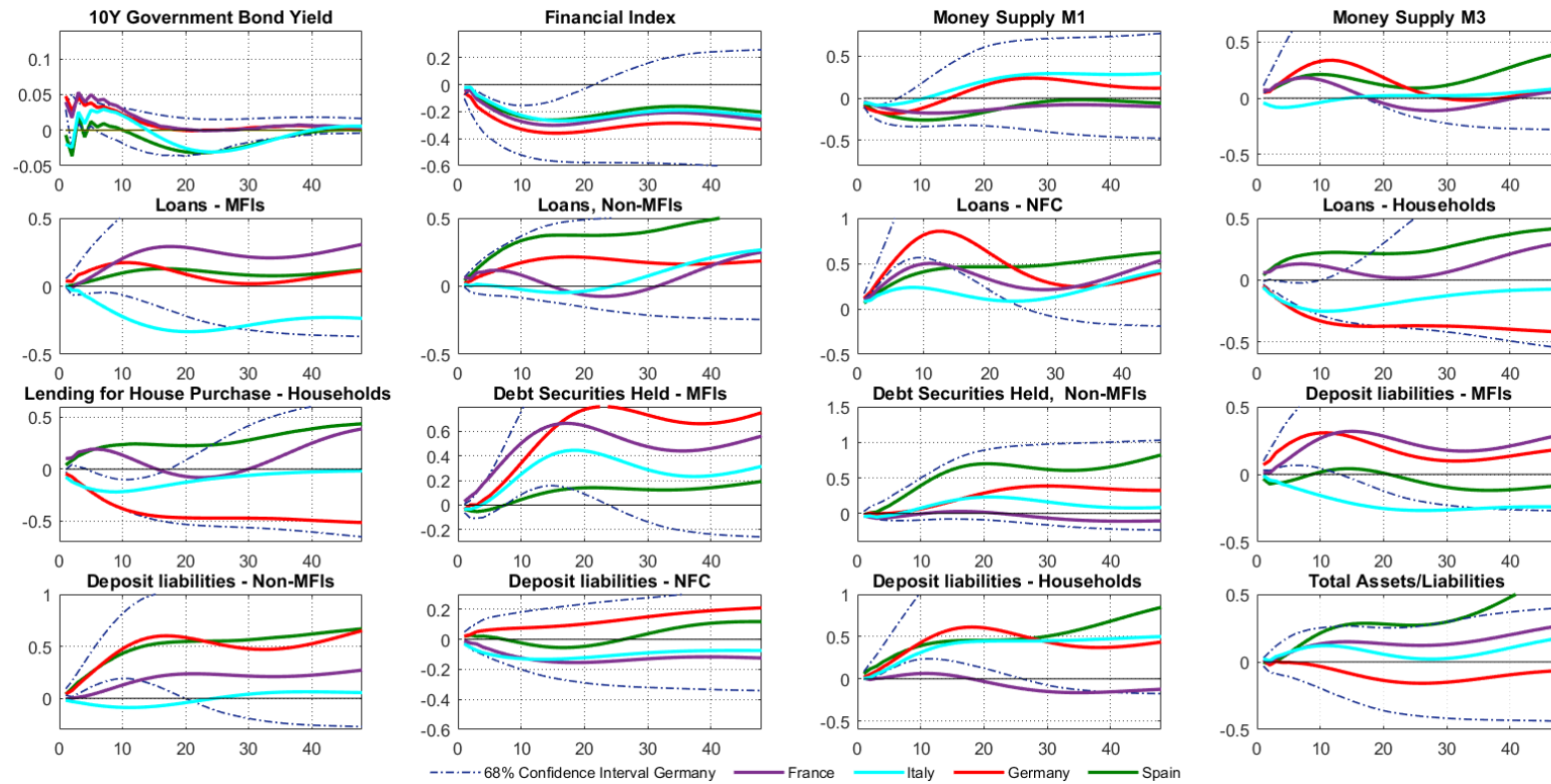
Figure 8: Rolling Windows 2005:9-2013:7 – Two Step FAVAR
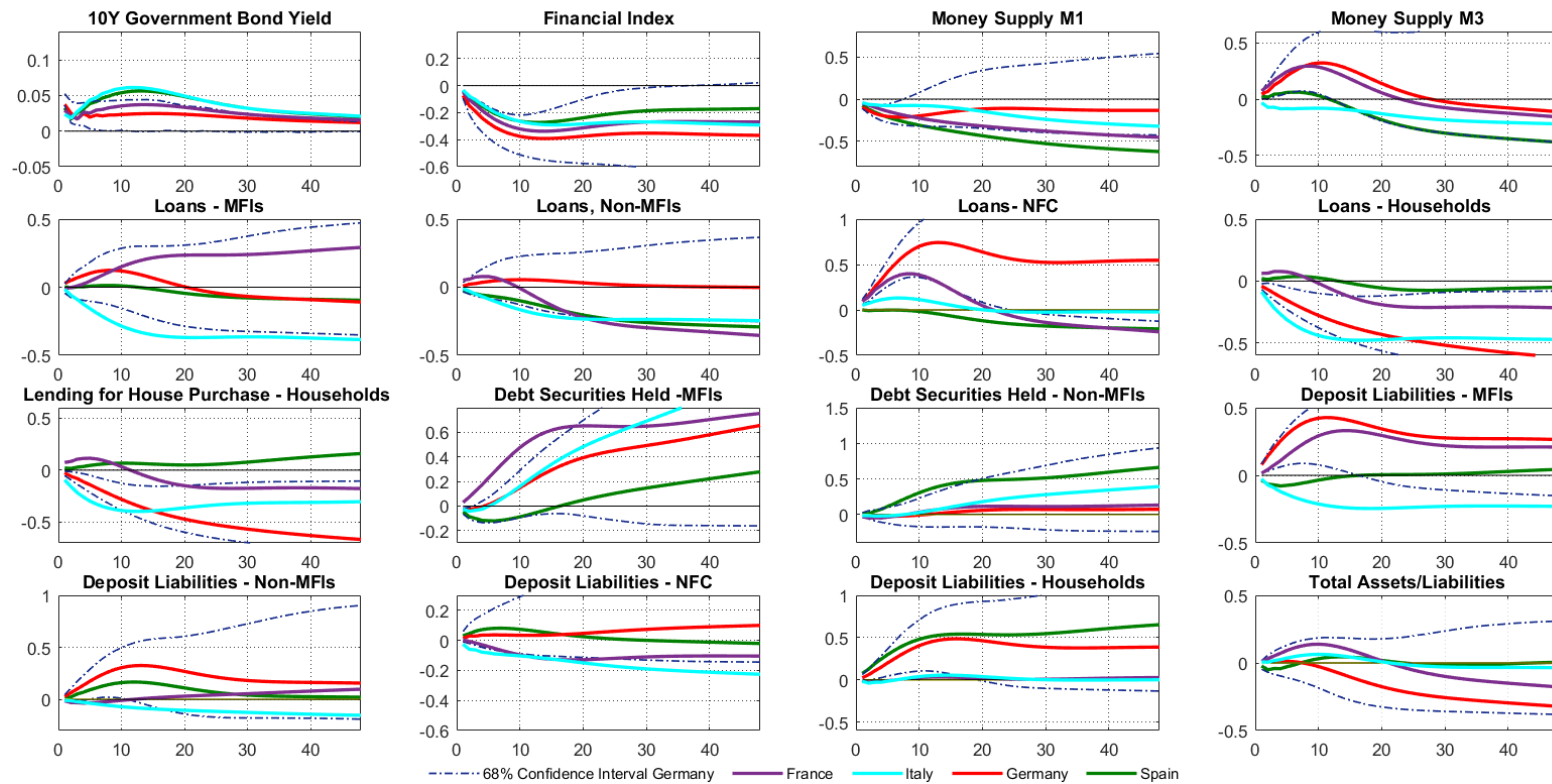
Figure 9: Rolling Windows 2006:9-2014:7 – Two Step FAVAR

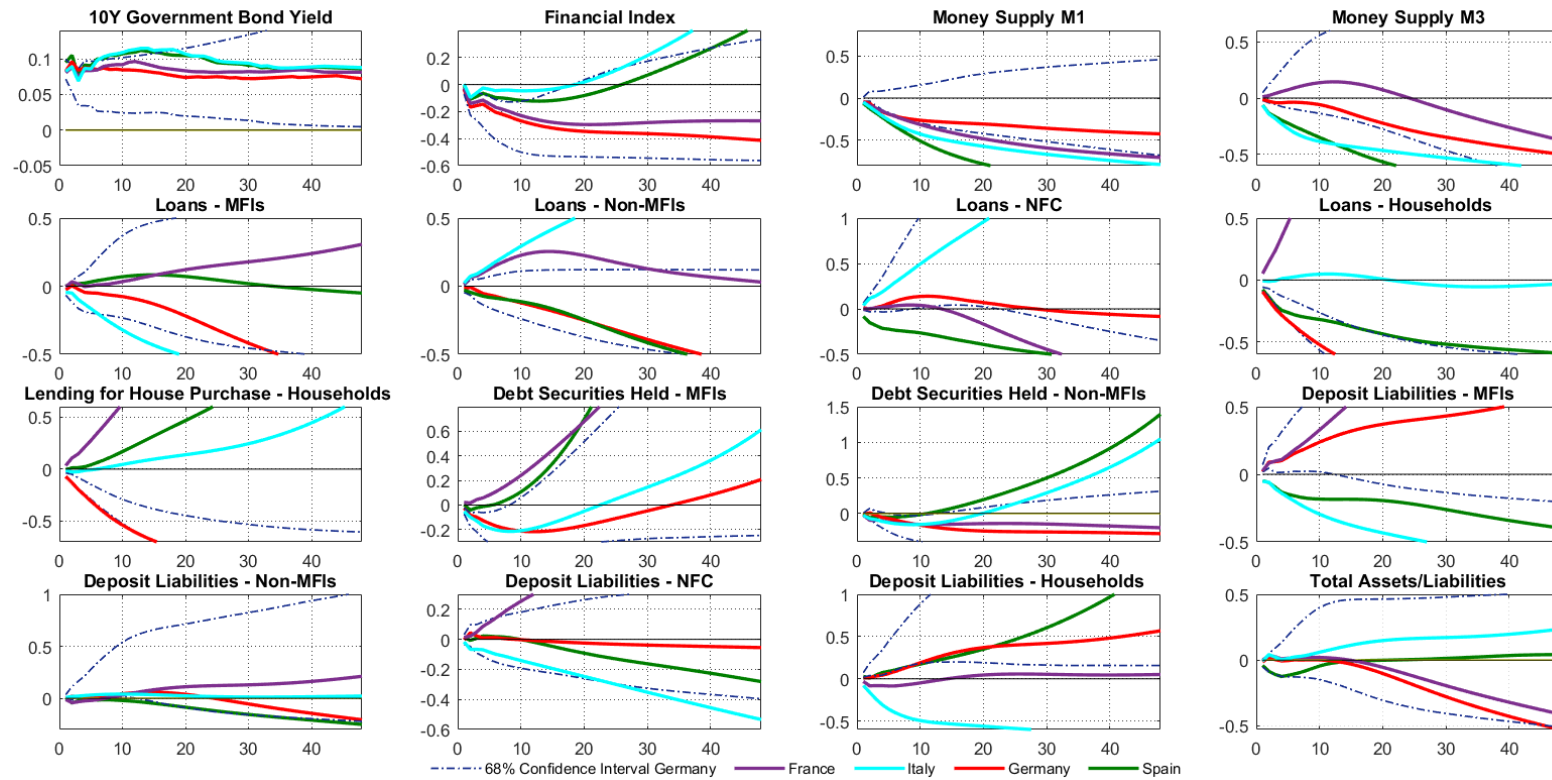*Figure 10: Rolling Windows 2007:9-2015:7 – Two Step FAVAR*

Figure 11: Rolling Windows 2008:9-2016:7 – Two Step FAVAR

Appendix F - Preliminary Master Thesis

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BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Heterogeneity in euro-area monetary policy transmission: results from a large multi-banking FAVAR model

ID number: 1002928, 1002929

Start: 01.12.2016 09.00

Finish: 01.03.2017 12.00

Neza Zemljic 1002929

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Preliminary Master Thesis

Heterogeneity in euro-area monetary policy transmission:

results from a large multi-banking FAVAR model

Hand-in date:

01.03.2017

Campus:

BI Oslo

Supervisor:

Barbara Bukhvalova

Examination code:

GRA 19502 – Preliminary Master Thesis

Programme:

Master of Science in Finance

2017

Table of Contents

Introduction

Understanding the transmission mechanism is crucial for the monetary policy of financial regulators around the world. Correspondingly, the role of banking institutions in this mechanism has been studied extensively both at a theoretical and an empirical level. In particular this has been the case, after the financial stability has once again become the focal point among academics following the global financial crisis of 2007/08.

The European Monetary Union (EMU) has in this regard been the prime source of interest, given the heterogeneous nature of both the sovereign states and banks composing the integrated system. While some degree of national differentiation is considered a normal feature of a monetary union, the heterogeneity in conditions across the euro area increased significantly in recent years. Primarily, as a result of the differences in the accumulation of fiscal, macroeconomic, and financial imbalances through the entire union in the period ahead of the crisis (Barnes, 2010). Although earlier on, financial integration and appropriate functioning of macro-financial linkages had ensured that the monetary policy of the ECB would transmit homogeneously to the whole euro area, since the crisis, the interconnections between market segments have largely broken. As a result, the ECB has been operating in a context of heterogeneity and segmentation in the financial markets, in terms of credit developments, financial fragility of borrowers, lenders and real activity (Ciccarelli, Maddaloni, Peydró, 2013).

Hereof, the aim of our master thesis is to fill the gap in the existing literature in relationship to the heterogeneous response of banks to single monetary policy. To empirically examine this connection, we analyze the response of the four largest EMU banking systems, following a common monetary policy shock. The main questions that we try to address are: How are monetary policy shocks transmitted to banking systems and, in particular, to bank equity prices? What are the sources of bank heterogeneity? What explains differences in individual banking system responses to monetary policy shock?

In order to provide a broad overview of the key issues associated with monetary policy transmission, we adopt an empirical approach and we re-examine the evidence concerning the propagation mechanism of monetary policy on banking activity. To perform the analysis, we closely follow Chetan and Dressler (2009), who examine the role of commercial banks in monetary policy transmission for the US banking system. In addition, we consider the work of Bernanke, Boivin, and Eliasz (2005), specifically the utilization of factor models for forecasting applications and structural analysis for testing the predictions of macroeconomic theory[1]. The authors succeed in developing a recurrent trend in the macroeconometric literature, which has led to an increase in the interest in the application of factor-augmented vector autoregressive (FAVAR).

Following the work of Bernanke et al. (2005), we test for heterogeneity in the responses of the four major banking systems of the EMU, subsequent to a standardized shock that corresponds to a 25-basis-point increase in the ECB official refinancing operation rate (REFI). In order to track the changes on an aggregate level, we constructed indexes for all four major European banking systems (Germany, Italy, Spain and France), while including both aggregated monthly bank-level and macro-level data, ranging from 2000 to 2017. The banks composing the respective systems will be selected according to similar criteria as for the Single Supervisory Mechanism, namely the asset value of each bank needs to exceed € 30bn. The size of the financial institutions is clearly the most important criterion for the banking sample, and as emphasized by Drehmann and Tarashev (2013), a relatively large size goes hand in hand with increased complexity, denser financial links, and a sufficient market share to trigger asset fire sales in the event of financial difficulties.

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[1] For forecasting applications see, e.g., Stock and Watson (2002a), Stock and Watson (2002b), Eickmeier and Ziegler (2008). While in regard to structural analysis see, e.g., Baumeister, Liu, and Mumtaz (2010).

Moreover, after imposing a small set of restrictions on the response of a few selected indicators, we will obtain the dynamic effects of monetary shocks and test the following;

I.   **Hypothesis 1:** Transmission of monetary policy shocks is heterogeneous across bank equity prices for German, Italian, Spanish, and French banks.

II. **Hypothesis 2:** Transmission of monetary policy shocks is heterogeneous across bank equity prices for the best capitalized banks in Germany, Italy, Spain, and France.

III. **Hypothesis 3:** Transmission of monetary policy shocks is heterogeneous among the stressed banks in the core and unstressed banks in the periphery of Europe.

IV. **Hypothesis 4:** Banking sectors that are more exposed to sovereign and banking stress react more abruptly to monetary policy shocks.

Literature review

In this section we provide an overview of earlier studies and relevant theories. Based on past literature we present valuable insight into the research topic, how previous work has addressed similar questions, and how the thesis plans to fill a gap in the existing literature.

The literature on monetary policy transmission and the effects of monetary policy shock is abundant and continually expanding. Over the years, several approaches have been employed in order to understand the propagation of monetary policy to both the economy and banking system. Among others, Dynamic Stochastic General Equilibrium (DSGE) models, (Structural) VARs and FAVARs are consistently used, with various degrees of success.

For the DSGE literature, a representative paper is the one by Smets and Wouters (2005), who based on the work of Christiano, Eichenbaum, and Evans (2001), were able to find results comparable to the ones originating from empirical VARs. The authors made a remarkable contribution to the DSGE literature, as they built a model able to study monetary policy in an empirically plausible setup. At the same time, Peersman and Smets (2003) analyzed the responses of several financial and macroeconomic variables to a hawkish monetary policy disturbance, while adopting a VAR approach. More recent papers include Sousa and Zaghini (2006) and Weber, Gerke, and Worms (2009). The first analyzed the impact of monetary policy shock through a SVAR approach, while the second performed an area-wide study on monetary policy transmission within a VAR framework.

Development of the FAVAR models

Since the groundbreaking work of Sims (1980), vector autoregressive (VAR) models became widely used scheme for analysis of monetary policy shocks and their effects on macroeconomic variables. As highlighted by Bernanke et al. (2005), these relatively simple approaches in general provide plausible results, indicating the dynamic responses of main variables to monetary policy innovations, without a necessity to identify the entire macroeconomic model.

Despite all the advantages, VAR does not lack for criticism. For instance, there is no consensus among researches about the appropriate scheme for identifying policy shocks. Another issue is that VAR only considers unanticipated changes in monetary policy. As highlighted by Sims and Zha (1998), most of the policy changes are systematic. VAR does not consider this systematic component and consequently the effect of monetary policy shock is underestimated. Moreover, many additional critiques refer to relatively small size of data used by low-dimensional VARs. To preserve degrees of freedom, VARs include only reduced number of macroeconomic variables. As pointed out by Bernanke et al. (2005), at most six to eight variables are engaged. Contrary, central banks follow a large set of information. This implies that it is necessary to consider that the results obtained by this method can be biased, due to omission of the relevant variables. Typical illustration of this potential issue is the price puzzle, explained by Sims (1992), when unexpected monetary tightening leads to increase in inflation in the impulse response function of the model, instead of a decrease as standard economic theory, intuition and empirical evidence would suggest.

With the purpose of resolving the issue with the use of VAR, Bernanke et al. (2005) introduced a way to adjust VAR analyses of monetary policy on richer information set, without losing the degrees of freedom in the model. They integrated the standard VAR analysis with factor analysis, wherein the aspect of small number of estimated factors being able to effectively summarize the information from a large number of time series, was exploited. Specifically, in the

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newly formed factor-augmented vector autoregressive (FAVAR) models, standard VAR models were enriched with a few estimated factors, carrying a large fraction of information about the economy and preserving the degrees of freedom.

It's important to note that only a small set of empirical papers investigate the impact of monetary policy shocks on bank performance, while applying an augmented vector autoregression (FAVAR). Therefore, taking everything into consideration we are lead to believe that the closest research to ours is that of Chetan and Dressler (2009), who analyzed the lending response of commercial banks in the US, by adopting a FAVAR approach. As such, their analysis relies on the applied literature that had aspired to identify the role of both bank heterogeneity and loan supply effects at the micro level data. Moreover, the empirical evidence purposed is restricted on testing the interaction of monetary policy variables with bank liquidity and capitalization levels, as they are both important determinants of loan growth.[2] Other related literature on changes in banking behavior following a monetary policy shock include the work of Kashyap and Stein (2000), Hannan and Berger (1991) and Berger and Udel (1992).[3]

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[2] see e.g. Kashyap and Stein, (2000).

[3] In this regard Kashyap and Stein (2000) analyse the impact on bank lending volume. Hannan and Berger (1991) investigates the impact on the deposit rates. Berger and Udel (1992) investigate the impact on the loan rates.

Contribution

Although several authors in the past addressed the topic of bank heterogeneity and the implications of monetary policy shocks in banking, the literature manly focuses on the effects of monetary policy on the bank lending channel (BLC). Therefore, we believe that some important considerations pertaining to the effects of monetary policy shocks have not been recognized or examined, especially in relation to changes in bank equity prices and risk. To the extent of our knowledge there are no studies employing the FAVAR approach in the context of heterogeneity of the banking systems. Furthermore, the current literature mainly focuses on data parenting to the U.S., while employing only bank-level variables on the monetary policy (Chetan and Dressler (2009)) or only a restricted number of variables (specific to the VAR approach). Hence, given the purposed approach and the existing gap in the literature, we believe that several contributions can be made.

First, we are lead to believe that we can considerably contribute to the existing literature, by providing an alternative methodological investigation for the analysis of bank behavior in response to MPS. As already mentioned in the previous segments, the current literature already addresses the question for bank heterogeneity. In consideration of the foregoing, however, these analyses only discuss the possible implications for the bank lending channel. In this respect, our aim is to develop a more comprehensive assessment of bank responses, following a monetary policy shock in the euro area. In order to do so, the evaluation will include both bank equity prices and risk, which to our best knowledge were never before been analyzed in the context of a FAVAR.

Second, the FAVAR framework allows for the inclusion of a large number of banking time series, in combination with a large panel of banking data. One major benefit of the addition of a larger number of variables is the possibility to study the systematic portion of monetary policy or the choice of monetary policy rule. For instance, previous literature based on a VAR approach is not able to address the latest, as it can only account for the effects of unanticipated changes in

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monetary policy. Correspondingly, a FAVAR model should better allow exploiting the co-movement in the responses between all four banking systems, in comparison to standard VAR literature.

Third, in the past FAVAR models have been fitted to large macroeconomic[4] and aggregate financial datasets.[5] The methodology, however, allows exploiting even richer information in its application. In this regard, we should be able to prove that omitting bank-level information leads to different estimates of impulse responses and shocks. To attest for the reasoning a gradual preclusion of specific banks will be performed in the sample. In addition, by adopting a rolling windows approach, we should be able to explore the time variation and the impact of the crisis on the heterogeneity.

Lastly, previous papers that are not adopting a VAR or FAVAR approach address the issue that monetary policy is endogenous by either approximating monetary policy by foreign policy rates or Taylor-rule gaps (Altunbas, Gambacorta, and Ibanez 2009). Hence, the macroeconomic variables might reflect the transmission of different types of shocks (eg. macroeconomic, oil, volatility, etc.). On the other hand, our analysis considers that the identified monetary policy shocks are orthogonal, which allow us to better divide the common drivers of banking sector developments.

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[4]E.g. see Bernanke, Boivin, and Eliasz (2005)

[5] E.g. see Nicolo and Lucchetta (2011)

Monetary Policy Shocks in the Euro Area

It is currently the most common approach, to interpret a monetary policy shock as a presence of measurement errors in the series used for decision making authorities (Bernanke and Mihov (1995)). Otherwise stated, we may define that MPS arise as "errors of assessment of the economic situation"[6] by the central banks. Nevertheless, there are two additional interpretation of monetary policy shock. The first regards the MPS defined as a preference shift from the part of the monetary authority. Concurrently, the second argues that the monetary authority, tends to avoid the social costs of frustrating agent expectations and that a change in these expectations can lead to an exogenous shock[7].

Identification of monetary policy shock

In order to best identify monetary policy shock, the work of Christiano, Eichenbaum and Evans (1998) was closely followed. The three authors, who present different identification schemes in the existing literature, argue that the recursive hypothesis in a VAR approach is a common way to identify monetary policy shock. The standard assumption in the purposed setup, is for the shocks to be orthogonal to the information set used by the monetary authority. Furthermore, in order to classify the variables a set of classifications has to be imposed. The first of these classifications consists of variables that comprise the information set and respond to monetary policy, with a delay of at least one time period. The second group consists of the variables that only include the operational monetary policy instrument. The final group is comprised of the variables that respond to the shocks contemporaneously.

In our analysis, we will assume a standardize shock, which will correspond to a 25-basis-point increase in the ECB official refinancing operation rate (REFI).

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[6] Uhlig (2005, p.398)

[7] E.g. see Chari, Christiano and Eichenbaum (1998)

Methodology

In the following section, we will algebraically present the model and describe the adopted econometric scheme that will be followed in order to obtain the results of this analysis. Specifically, we will discuss the estimation process of our empirical model, define an impulse response function and present the identification approach. In every step, we closely follow the procedures proposed by Bernanke et al. (2005).

Econometric framework

Let Y_t be a $M \times 1$ vector of observable economic indicators assumed to drive the dynamics of economy, and t be a time index, $t = 1,2 \ldots, T$. In like manner, let us suppose that additional economic information, not fully captured by Y_t but potentially relevant to model the dynamics of these time series, can be compiled by a $K \times 1$ vector of factors, F_t, where K is "small". The joint dynamics of (F_t, Y_t) is summarized as follows:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + u_t, \quad E(u_t' u_t) = Q \tag{1}$$

where $\Phi(L)$ is a conformable lag polynomial of finite order d, and u_t is a $(K + 1)$ column vector that $u_t \sim i.i.d. N(0, Q)$.

Equation (1) represents the factor augmented vector autoregressive model in (F_t, Y_t). Due to unobservability of the factors F_t, equation (1) cannot be estimated directly. However, Bernanke et al. (2004) propose that unobserved factors can be extracted from "informational" time series included in $N \times 1$ vector of X_t. We may think of it as central banks' information set, consequently N is a large number, particularly greater than the number of time periods T. Moreover, X_t is assumed to be much greater than the number of factors and observed indicators in FAVAR system. (For concreteness, we assume $N > T$ and $N \gg K + M$). Informational time series X_t are assumed to be related to the unobservable factors F_t and observable indicators Y_t by the following observation equation:

$$X_t = \Lambda^f F_t + \Lambda^y Y_t + e_t, \quad E(e_t' e_t) = R \tag{2}$$

where Λ^f is an $N \times K$ matrix of factor loadings, Λ^y is $N \times M$, and e_t is an $N \times 1$ vector of mean-zero error terms.

"Equation (2) captures the idea that both Y_t and F_t, which in general can be correlated, represent common forces that drive the dynamics of X_t."[8] The error terms in equation (1) and (2) are presumed to be independent, and R is a diagonal matrix.

Estimation

Bernanke et al. (2005) suggests two estimation procedures. The first is a one-step method, which employs Bayesian likelihood and Gibbs sampling techniques in simultaneous estimation of the factors and the FAVAR model. The second is a two-step principal component approach, "which provides a non-parametric way of uncovering the space spanned by the factors of X_t."[9] Bernanke et al. (2004) emphasize that these approaches differ in various dimensions, nonetheless there are no explicit a priori reasons why one approach should be favored over the other. Due to its computational simplicity, we opted to follow the two-step approach, in order to estimate our empirical model. Intricacies of the method are summarized in the following subsection.

Two-step principal components estimation approach

In the two-step approach, the both factors in equation (2) and FAVAR model represented by equation (1) are estimated separately. Parallel to the forecasting exercises of Stock and Watson (2002b), the first step of the procedure is applied to equation (2) in aim to estimate the space spanned by the factors. For this purpose, the first $K + M$ principal components of X_t, denoted by $\hat{C}(F_t, Y_t)$, are used. It is important to point out that the estimation of this step does not employ the

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[8] Bernanke et al. (2005, p.393).

[9] Bernanke et al. (2005, p.398).

observed factors Y_t. However, as emphasized by Bernanke et al. (2005, p. 398), and presented by Stock and Watson (2002b), the principal components both consistently and regularly recover the space spanned by both F_t and Y_t as long as N is large and the number of used principal components is at least as large as the true number of factors. Otherwise stated, principal components are engaged in the first step of the procedure, with the intent to estimate factors $(\widehat{F_t^1}, \widehat{F_t^2}, \ldots, \widehat{F_t^K})$ from the equation (2). Given the assumption of R being diagonal in (2), the approach employs OLS in aim of obtaining the estimates of factor weights $\left(\widehat{\Lambda_1^f}, \widehat{\Lambda_2^f}, \ldots, \widehat{\Lambda_K^f}\right)$. In the second step, the unobserved factors in (1) are first replaced by their principal component estimates, and in aim of obtaining $\widehat{\Phi}(L)$, a standard VAR approach;

$$\begin{bmatrix} \widehat{F_t^1} \\ \widehat{F_t^2} \\ \vdots \\ \widehat{F_t^K} \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} \widehat{F_{t-1}^1} \\ \widehat{F_{t-1}^2} \\ \vdots \\ \widehat{F_{t-1}^K} \\ Y_{t-1} \end{bmatrix} + e_t$$

is imposed. The main advantages of the procedure are its computational simplicity, ease of implementation, allowance of some degree of cross-correlation in the idiosyncratic term e_t and that it imposes only a few distributional assumptions. However, the approach implies the presence of "generated repressors" in the second step and thus it necessitates the implementation of a bootstrap procedure that accounts for the uncertainty in the factor estimation. With the implementation are obtained the accurate confidence intervals on the impulse response function. Similarly to the related FAVAR literature, our analysis will implement bootstrapping procedure proposed by Kilian (1998).

Impulse response function

One of the previously mentioned advantages of FAVAR methodology, over standard VARs is the ability of controlling impulse response analysis on a larger amount of factors. Following Blaes (2009), impulse response functions of $\widehat{F}_t$ and Y_t are given by,

$$\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \psi(L)u_t$$

(3)

where $\psi(L) = [I - \phi_1 L - \cdots - \phi_d L^d] = [I - \Phi(L)]^{-1}$.

By combining equations (2) and (3), the following transformation is obtained:

$$X_{it}^{IRF} = [\widehat{\Lambda^f} \quad \widehat{\Lambda^y}] \begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = [\widehat{\Lambda^f} \quad \widehat{\Lambda^y}][\psi(L)u_t] \tag{4}$$

The equation (4) enables the formation of impulse responses for any element X_{it} of X_t. It is crucial to specify that equation (4) exhibits the impulse response function to innovations in u_t. However, the main aim of the analysis is to study the responses of the variables of interest to structural, e.g. monetary policy shocks. Hence, it is essential to identify the relationship between the reduced form and structural shocks. Given the reduced-form FAVAR in equation (1), we assume that an orthogonal and invertible matrix of dimension $(K + M) \times (K + M)$, called A, presents the contemporaneous relation between the variables in the FAVAR model.[10]

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[10] It is assumed by Sims (1980) that A is an invertible, lower triangular matrix with all elements on the main diagonal equal to 1. In case we assume a FAVAR model with N variables, the lower triangular structure implies $\frac{N(N-1)}{2}$ exclusion restrictions in the matrix. This signifies that A is exactly identified.

Consequently, when multiplying the reduced form with A^{-1}, the structural model can be acquired, implying the following linear relation between the structural shocks (ε_t) and the reduced-form innovations (u_t):

$$\varepsilon_t = Au_t \text{ or } u_t = A^{-1}\varepsilon_t \tag{5}$$

Thus, the moving average description of the structural form, analogous to the equation (3) is given as:

$$\begin{bmatrix} \widehat{F}_t \\ Y_t \end{bmatrix} = \psi^*(L)u_t \tag{6}$$

where $\psi^*(L) = \psi(L)A^{-1}$. Given these notations, the mission is to identify A, or in our case only a row of A, as the aim is the identification of a single monetary policy shock.

Identification

In contrast to standard VAR models, identification of the FAVAR is more complex. Primarily, because it requires the identification of the factor spaces, in addition to the identification of structural shocks in the model. "Since there is more than one structure of economic interest which can give rise to the statistical model for a vector of variables",[11] the identification issue can arise. The proposed solution is to put identifying restrictions on the structure where the number of parameters exceeds that in the reduced form. In our empirical analysis we follow the identification scheme and restriction implementation of Bernanke et al. (2005) and (2004), discussed in the following subsections.

Identification of the factors

There are two options for factor identification in FAVARs. First one is to impose the restriction on the observation equation, while the second one is to restrict the transition equation. Bernanke et al. (2005) prefer not to restrict the VAR

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[11] Favero (2001, p.85)

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dynamics, but to impose restrictions on factors and their coefficients in observation equation (2).

The authors suggest that adequate approach for factor identification in two-step estimation method is to either restrict coefficients by $\frac{(\Lambda^f)'(\Lambda^f)}{N} = I$ or restrict the factors by $\frac{F'F}{T} = I$. Both procedures provide the same common component $F(\Lambda^f)'$ and the same factor space.[12]

Identification of the monetary policy shock

In aim to identify a single shock in structural FAVAR model, Bernanke et al. (2005) introduced a scheme in which they part between "fast-moving" and "slow-moving" variables. While "fast-moving" variables are characterized as "highly sensitive to contemporaneous economic news or shocks", the "slow-moving" ones are as to be "largely predetermined as of the current period". Examples of "slow-moving" variables include output, employment and price series, while examples of "fast-moving" variables include interest and exchange rates as well as monetary aggregates.[13]

Shocks are assumed to be orthogonal to each other and normalized in order to have a unit variance ($E[\varepsilon_t \varepsilon_t'] = I$). In view of the relation between the reduce-form innovations and the structural shocks in (5), the covariance matrix of the former can be reformulated by following procedure:

$$Q_u = E[u_t u_t'] = A^{-1}E[\varepsilon_t \varepsilon_t']A^{-1'} = A^{-1}A^{-1'} \qquad (7)$$

Stock and Watson (2005), among others, proposed Cholesky decomposition of the covariance matrix Q_u as a credible solution for retrieval of ε_t and so for the precise identification of the system.

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[12] See Bernanke et.al (2005, p. 400-401) for more detailed explanation.

[13] See Bernanke et al. (2005) for a more detailed explanation of the criteria used to classify the variables.

The above mentioned decomposition is applied in the following manner: When $A^{-1} = C$, where C is the Cholesky decomposition of the covariance matrix Q_u, such that $CC' = Q_u$, the lower triangular structure of C supplies $\frac{N(N-1)}{2}$ free parameters as in (5). Based on this, the system is thoroughly identified.

Given the above described decomposition, Bernanke et al. (2005) propose the identification of the monetary policy shock in the standard recursive form which that is by ordering the policy instrument last, after the slow moving factors, and considering its alteration as the policy shock. The key identification assumption here is that the "slow-moving" variables do not respond contemporaneously to changes in policy variable. In contrast, the "fast-moving" variables are presumed to develop closely with the movement of the monetary policy instrument. In aim of preventing the collinearity in the structure, the authors eliminate these factors from their recursive form.

In order to implement the form in the two-step FAVAR model, further adjustments are needed. To regulate the part of the space spanned by the factors, i.e. $\hat{C}(F_t, Y_t)$, corresponding to the monetary policy variable Y_t, Bernanke et al. (2005) propose the following procedure: First, "slow-moving" factors, F_t^s, as the first K principal components of the "slow-moving" variables in X_t need to be estimated. Second, by estimating the following regression,

$$\widehat{C}_t = \beta_{F^s}\widehat{F_t^s} + \beta_Y Y_t + e_t$$

where $\widehat{F}_t$ can be obtained from $\widehat{C}_t - \widehat{\beta_Y}Y_t$. Note that as $\widehat{F_t^s}$ and Y_t are correlated, so are $\widehat{F}_t$ and Y_t. Finally, the FAVAR in $\widehat{F}_t$ and Y_t can be estimated and the monetary policy shock identified recursively using this ordering.

Data

In our empirical model, we will use two different sets of data: a bank-level one, and macroeconomic one. In this regard, the aggregated balanced panel will encompass 150 monthly time series, and span between the period of 2000 and 2016. This data were collected from a number of sources, including Bloomberg, Reuters, Factset, Eurostat and the Statistical data Warehouse.

The Same level data frequencies are usually adopted by authors for the estimation of a typical FAVAR models. For instance, Bernanke et al. (2005), among others, evaluate a monetary policy VAR adopting only monthly variables. Despite the popular approach, this estimation method discards potentially important variables that can only be observed at other than monthly frequencies. To illustrate, a monthly data approach leaves out real GDP, which is commonly accepted as the most accurate measure of economic activity. One possible solution is to aggregate monthly variables to a quarterly level and estimate the model on a quarterly frequency. However, then the quarterly model is subject to an aggregation bias, which implies that important information get lost in the aggregation process.

Macroeconomic data

In the macroeconomic set, we will among others include the following data series: industrial new orders and turnover, nonfarm payroll, consumption, price indices, exchange rates, short- and long-term interest rates, money and credit quantity aggregates, balance of payments and external trade, confidence indicators and in addition to a small set of foreign variables for US, UK and Japan used as proxies for external real, nominal and monetary influences.

Bank-level data

For our Bank-level variables, we will involve bank equity prices for all four major EMU economies, based on same criteria as for the Single Supervisory Mechanism (ECB, 2014), namely: Asset value in excess of €30bn or having received

European financial subsidies. By doing so, the set of banks should be large enough to fully represent the banking systems for Germany, Italy, Spain and France. According to Drehmann and Tarashev (2013), a relatively large size of banks goes hand in hand with increased complexity, denser financial links and sufficient market share to trigger a fire sale in the event of financial difficulties. Balance sheet items for the banking systems will include, among others, bank loans, return on assets and bank's capital ratio, non-performing loans to total loans, cash, syndicated loans, credit for consumption, debt securities held, revolving loans and overdrafts and credit default swaps.

References

Altunbas, Y., Gambacorta, L. and Marques-Ibanez, D. (2009). Bank risk and Monetary Policy, ECB Working Paper Series No. 1075.

Barnes, S. (2010). Resolving and Avoiding Unsustainable Imbalances in the Euro Area. OECD Economics Department Working Paper, No. 82.7.

Baumeister, C., Liu, P., and Mumtaz, H. (2010). Changes in the Transmission of Moneetary Policy: Evidence From a Time-Varying Factor-Augmented VAR. Bank of England Working Paper.

Berger, A., and Udell, G., 1992. Some Evidence on the Empirical Significance of Credit Rationing, Journal of Political Economy, University of Chicago Press, vol. 100(5), pages 1047-1077.

Bernanke,B. and Mihov, I. (1995). Measuring Monetary Policy, NBER Working Paper No. 5145.

Bernanke, B., Boivin, J., and Eliasz, P. (2004). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. NBER Working Paper No 10220.

Bernanke, B., Boivin, J., and Eliasz, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. Quarterly Journal of Economics, 120(1), pages 387-422.

Blaes, B. (2009). Money and monetary policy transmission in the euro area: evidence from FAVAR and VAR approaches. Deutsche Bundesbank Discussion Paper, Series 1: Economic Studies (18).

Ciccarelli, Maddaloni A. and Peydró, J. (2013). Heterogeneous transmission mechanism Monetary policy and financial fragility in the Euro area. ECB Working Paper Series, No. 1527.

Chetan, D. and Dressler, S. (2009). The Bank Lending Channel: a FAVAR Analysis. Journal of Money Credit and Banking, 45(4).

Christiano, L., Eichenbaum, M. and Evans, C. (1997). Modeling money, Working Paper Series, Macroeconomic Issues WP-97-17, Federal Reserve Bank of Chicago.

Christiano, L., Eichenbaum, M. and Evans C. (2001). Nominal Rigidities and the Dynamic Effectsof a Shock to Monetary Policy. NBER Working Paper No. 8403.

Drehmann, M. and Tarashev N., (2013). Measuring the System of Interconnected Banks, BIS Working Papers, No. 342.

Eickmeier, S. and Ziegler, C. (2008). How successful are dynamic factor models at forecasting output and inflation? A meta-analytic approach. Journal of Forecasting, 27:237-265.

Favero, C. (2001). Applied Macroeconomics. Oxford Univ. Press.

Hannan, T., and Berger, A. (1991). The Rigidity of Prices: Evidence from the Banking Industry American Economic Review, vol. 81, issue 4, pages 938-45.

Kashyap, A. and Jeremy, S. (2000). "What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?" American Economic Review, 90(3), pages 407-428.

Kilian, L. (1998). Small-sample confidence intervals for impulse response functions. Review of Economics and Statistics, 80(2), pages 218-230.

Nicolò, G. and Lucchetta M. (2011). Systemic Risks and the Macroeconomy, NBER Working Paper No. 16998.

Sims, C. (1980). Macroeconomics and reality. Econometrica, 48(1), pages 1-48.

Sims, C. (1992). Interpreting the macroeconomic time series facts: the effects of monetary policy. European Economic Review, 36(5), pages 975-1011.

Sims, C. and Zha, T. (1998). Does Monetary Policy Generate Recessions? Federal Reserve Bank of Atlanta.

Smets, F. and Peersman, G. (2003).The Monetary Transmission Mechanism in the Euro Area: More Evidence from VAR Analysis, ECB Working Paper No. 91.

Smets, F. and Wouters, R. (2005). Comparing shocks and frictions in US and euro area business cycles: A Bayesian DSGE approach. Journal of Applied Econometrics, 20(2), pages 161-183.

Sousa, J. and Zaghini, A. (2006). Global monetary policy shocks in the G5: A SVAR approach, CFS Working Paper Series 2006/30, Center for Financial Studies (CFS).

Stock, J. and Watson, M. (2002a). Forecasting using principal components from a large number of predictors. Journal of the American Statistical Association, 97(460), pages 1167-1179.

Stock, J. and Watson, M. (2002b). Macroeconomic forecasting using diffusion indexes. Journal of Business & Economic Statistics, pages 147-162.

Stock, J. and Watson, M. (2005). Implications of dynamic factor models for VAR analysis. NBER Working Paper No 11467.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification approach. Journal of Monetary Economics, 52(2), pages 381-419.

Weber, A., Gerke R. and Worms, A. (2009). Has the monetary transmission process in the euro area changed? Evidence based on VAR estimates, BIS Working Papers No. 276.